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From Ideation to Growth: The Impact of Generative AI on Entrepreneurial Processes in Qatar

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Abstract
This study investigated the impact of Generative Artificial Intelligence (GenAI) on entrepreneurial processes within Qatar's start-up ecosystem. Through a quantitative survey of 106 Qatari start-up leaders, the study examined the patterns of GenAI adoption, and its influence on innovation and growth, and the contextual barriers shaping these outcomes. The findings revealed that perceived usefulness is the strongest determinant of adoption, while ease of use plays a secondary role, extending Technology Acceptance Model (TAM) to incorporate ethical legitimacy and institutional readiness. Furthermore, regression results demonstrated a statistically significant and positive impact of GenAI adoption on innovation outcomes, especially in enhancing idea generation, rapid prototyping, and creative problem-solving. However, the relationship with growth performance is weaker, reflecting the impact of contextual factors such as market size, funding ecosystems, and regulatory frameworks. Theoretically, the study contributes to an integrated framework that synthesizes existing models in an attempt to provide a more holistic explanation in GenAI adoption in culturally embedded and state-led ecosystems. In terms of practical applications, the research carries implications for Qatari entrepreneurs modelled by strategies such as phased adoption and hybrid human-AI models and for policymakers with recommendations such as using data to better refine regulation, capacity-building and trust building measures.

Keywords: GenAI, Technology Adoption Model (TAM), Innovation, Start-up ecosystem, Qatar

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1. Introduction

The development of Generative Artificial Intelligence (GenAI) signals a significant transformation in organizational approaches to innovation, operation efficiency, and sustaining competitive edge. Whereas traditional automation systems are designed primarily to replace routine activities, GenAI augments human capability and supports strategic decision-making by generating novel content – including text, images, codes, and analytical insights – through the application of advanced pattern recognition techniques developed from extensive historical data (Mariani and Dwivedi, 2024). Kusetogullari et al. (2025) argue that the rise of GenAI positions technology as a creative partner, amplifying entrepreneurial potential rather than serving as a replacement for human labor. The unprecedented scale of the adoption of tools such as ChatGPT, Google Gemini, and Microsoft Copilot in content generation, idea validation, marketing automation, and customer engagement underscore GenAI's role within organizational processes (Dwivedi et al., 2023; Gartner, 2024). These developments have catalyzed a restructuring of entrepreneurial practices, prompting start-ups to reimagine their business models around AI-enabled innovation.

In Qatar, this transformation is aligned with national priorities of economic diversification under the Qatar National Vision 2030 (GSDP, 2008) in which digital innovation and AI are identified as key drivers of a knowledge-based economy (MCIT, 2024). Projections indicate that Qatar's AI industry is poised for significant growth, expanding from USD 9 million in 2020 to an estimated USD 730 million by 2031—a nearly 23-fold increase (Statista, 2025). Over the same period, the number of AI users in the country is expected to rise dramatically from around 16,000 to 270,000, representing a 17-fold surge by 2031. This rapid trajectory positions Qatar among the most dynamic emerging AI markets globally. GenAI has two implications for Qatari entrepreneurs. It offers scalable tools for ideation, prototyping, and customer engagement that can help lean start-ups compete in spite of their resource limitation. However, adoption depends on regulatory frameworks, cultural legitimacy and institutional support mechanisms, which requires a systematic empirical investigation.

Despite the global emergence and rapid growth of GenAI, its potential consequences on entrepreneurial processes in emerging markets like Qatar remain underexplored. Much of the existing research centers on developed economies and established corporations (Dwivedi et al., 2023; Singh et al., 2024), often neglecting state-driven, culturally embedded ecosystems where government intervention significantly shapes entrepreneurial outcomes (Chalmers et al., 2021). Three major gaps impede both theoretical development and practical implementation: First, there is a scarcity of quantitative studies examining patterns and outcomes of GenAI adoption within start-up ecosystems in emerging markets. Second, conventional technology adoption models—such as the Technology Acceptance Model and Diffusion of Innovation—fall short in addressing GenAI's inherent uncertainty, rapid evolution, ethical complexities, and iterative learning processes (Gupta and Yang, 2024; Dwivedi et al., 2023). Third, entrepreneurs lack empirically tested models to assess the benefits and risks of GenAI adoption, especially in the context of Qatar's evolving regulatory and socio-cultural environment. This research seeks to address these gaps by offering empirical insights into GenAI adoption among Qatari start-ups, analyzing the impact of GenAI on entrepreneurial processes and building contextualized theoretical models.

The primary research objective of this research is as follows: "*How does Generative AI influence the entrepreneurial process in start-ups in Qatar, and what factors contribute to its impact?"*. The study further examines the factors that affect GenAI adoption patterns among Qatari start-ups across different sectors and developmental stages. It examines the integration of GenAI technologies in the different stages of the entrepreneurial process and the opportunities, risks, and challenges faced by founders in the overall implementation process. Finally, it considers how the existing theoretical frameworks can be better adapted to explain GenAI adoption in the entrepreneurial ecosystem in Qatar. This research has four interrelated objectives. First, it seeks to investigate how start-ups in Qatar leverage GenAI in different business functions and entrepreneurial processes. Second, it aims to explore the role of GenAI in boosting entrepreneurial stages using the theoretical framework of Experiential Learning Theory by analyzing the role of repeated cycles of learning in the integration of technology and development of businesses. Third, it evaluates the economic and social benefits and hurdles entrepreneurs encounter by incorporating Generative AI in start-up operations. Fourth, it identifies practical paths forward for entrepreneurs, educators, and policymakers that may be used to maximize GenAI usage in Qatar's emerging entrepreneurial ecosystem.

From an academic standpoint, this study is an extension of the scarce research on GenAI adoption in emerging economies through testing and extending frameworks including the Technology Acceptance Model (TAM), the Resource-Based View (RBV), Dynamics Capabilities (Teece, 1997), and Experiential Learning Theory (Kolb, 1984). It illustrates that the outcomes of adoption are influenced by factors of perceived usefulness, ethic legitimacy, regulatory framework and institutional trust. Practically, the study offers evidence-based guidance to Qatari entrepreneurs such as phased adoption strategies, AI-readiness assessments, and hybrid human-AI operating models for innovation enhancement in countering the risks such as ideation, integration costs, skill shortages, and regulatory uncertainty (Albous et al., 2025). At the policy level, this research aligns with the objectives of Qatar National Vision 2030 and the National Artificial Intelligence Strategy (NAIS) 2031 (MCIT, 2024) by providing data-driven insights that can inform the refinement of regulatory frameworks and strengthen capacity-building initiatives. Ethical issues, including data privacy, fairness, and cultural sensitivity (Mittelstadt et al., 2016), are highlighted as central to responsible AI deployment.

This study is geographically restricted to the start-ups operating in Qatar. Organizationally, it is based on small to medium-sized start-ups at an early and growth stage. Technologically, it is limited to Generative AI applications and not the broader fields of AI (Dwivedi et al., 2023). Large corporations are excluded because of resource structure and decision-making differences. Methodologically, the study adopts a quantitative design for the research process, which allows for generalization across the Qatari start-up ecosystem, resulting in findings that are both empirically robust and practically applicable (Creswell and Creswell, 2017). Overall, the paper is arranged in the following manner. Following this is a section on relevant literature pertaining to GenAI. The third section presents the research philosophy guiding the study and data sources. The fourth section discusses the findings of the study. The final section concludes with policy recommendations and future areas of research.

2. Review of Literature

The overlapping of entrepreneurship and Generative Artificial Intelligence (GenAI) has emerged as one of the most disruptive elements transforming current business environments (Dwivedi et al., 2023). The phenomenal growth of GenAI tools since 2022 has revolutionized the entrepreneurial views about innovation and resource allocation. However, current academic discourse highlights substantial limitations in exploring the opportunities and risks associated with this shift (Dwivedi et al., 2023; Nambisan, 2017; Von Briel et al., 2018). These limitations are especially evident in emerging economies like Qatar, where the adoption process is influenced by institutional and cultural factors (Al-Kwifi et al., 2020). Three major gaps emerge. First, studies focus on the positive implications of GenAI while under examining ethical concerns, regulatory ambiguities or skill loss (Mittelstadt et al, 2016; Binns, 2018). Second, context-specific research in GCC economies is still limited in spite of unique regulatory and socio-cultural environment (Al-Kwifi et al., 2020). Third, coherent frameworks explaining GenAI adoption in entrepreneurial settings are lacking. Entrepreneurship has moved away from the view of a static process driven by resource availability to the view of a dynamic process influenced by technological and institutional forces (Bygrave and Hofer, 1991; Shane and Venkataraman, 2000). In Qatar, this evolution is accelerated through state-driven digital transformation agendas through Qatar National Vision 2030 (GSDP, 2008). Entrepreneurship as innovation (Schumpeter, 1934), opportunities recognition (Shane and Venkataraman, 2000) and new venture creation (Gartner, 1985). However, the discovery-exploitation framework assumes that there are opportunities independent of entrepreneurs (Alvarez and Barney, 2007). In technology-driven situations, opportunities are created increasingly by interacting with the new tools (Nambisan, 2017).

GenAI strengthens this view of creation. Often, AI-driven opportunity formation processes go hand in hand with analytics and automation (Von Briel et al., 2018; Li et al., 2021). GenAI accelerates the processes of ideation, prototyping, and decision-making (Dwivedi et al., 2023), thereby challenging the traditional linear innovation model—particularly in volatile and uncertain environments (Bennett and Lemoine, 2014). Traditional stage models – opportunity recognition, resource marshaling and venture launch (Bygrave and Hofer, 1991) – fail to capture GenAI enabled entrepreneurship. Sarasvathy's (2001) effectuation theory suggests that entrepreneurs start with the available means instead of predetermined goals and create opportunities through iterative experimentation (Dwivedi et al., 2023). GenAI helps decrease the experiments and shrinks the development timelines (Von Briel et al., 2018), however, current models fail to understand the re-organizational impact AI and GenAI have on the "means" and "ends" equation. In the case of Qatar, policy pressures make this nonlinearity stronger, which adds to the need for context-sensitive analysis. A major debate is the conflict between planning and emergence of GenAI. GenAI improves predictive capabilities and at the same time also improves the experimentation speed (Nambisan, 2017; Dwivedi et al., 2023). While digital transformation literature emphasizes the reduced costs associated with iterative processes (Brynjolfsson and McAfee, 2014), it tends to under-theorize the risks introduced by GenAI, such as ethical, operational, and societal concerns (Mittelstadt et al., 2016; Binns, 2018).

In Qatar's relationship-orientated business culture, tensions between the fast development of AI and traditional norms remain underexplored (Al-Kwifi et al., 2020; Zahra, 2007). Unlike traditional AI, GenAI produces new content using transformer architectures and large language models (Haenlein and Kaplan, 2019; Bommasani et al., 2021). The 2022 breakthroughs meant that accessibility to under-resourced entrepreneurs is no longer limited. In Qatar, these technologies are in line with National AI Strategy 2031 (MCIT, 2024), but regulatory ambiguity is limiting adoption of GenAI. GenAI is applicable across all stages of entrepreneurship, spanning from idea generation to business scaling. It improves the creative synthesis and recognition of data-driven opportunities (Gans et al., 2019; Cockburn et al., 2018). Although this aligns with the Resource-Based View (RBV) (Barney, 1991), the widespread availability of GenAI technologies may diminish their rarity as a source of competitive advantage (Zhang et al., 2023). In Qatar, cultural and linguistic market requirements, local buy-in becomes imperative (Albous et al., 2025). In the market analysis, GenAI democratizes the advanced analytics (Cockburn et al., 2018) but is limited by regulatory and data fragmentation in Qatar (Villegas-Mateos, 2023; Albous et al., 2025). In product development, it lowers the technical barriers (Dwivedi et al., 2023; Li et al., 2021) that make the products more accessible but also more competitive. In terms of customer engagement, there is enabling of large-scale interactions (Haenlein and Kaplan, 2019) but trust is the key in the relational culture of Qatar (Zahra, 2007).

GenAI results in efficiency, reduces organizational operational costs and contributes to lean organizational models (Brynjolfsson and McAfee, 2014). Routine tasks can be automated that can allow the entrepreneurs to focus on strategic and relational capabilities (Barney, 1991; Ali et al., 2024). For Qatari start-ups that struggle to keep operations running due to high costs and a lack of skills, such resource reallocation is especially valuable. Technical challenges get in the way of effective integration (Amershi et al., 2019). Regulatory uncertainty in Qatar (MCIT, 2024) creates compliance risks (Mittelstadt et al., 2016). Deskilling concerns are also relevant, as overreliance on GenAI may erode strategic competencies (Barney, 1991; Alet, 2024). Cultural misalignment and algorithmic bias represent a further threat to legitimacy (Bender et al., 2021). GenAI helps in faster innovation cycles and shortens the time-to-market (Cockburn et al. 2018; Dwivedi et al. 2023). Automation enhances both scalability and the quality of customer interactions (Li et al., 2023). From a financial perspective, cost reductions and lean organizational structures contribute to stronger competitive positioning, supporting Qatar's economic diversification agenda (MCIT, 2024). The adverse effects of automation include lack of human capital (Barney, 1991). Cultural misalignment poses the risk of damaging the reputation (Bender et al., 2021). Regulatory uncertainty creates more of an ambiguous policy-based environment (MCIT, 2024). Variation in sectors is significant with FinTech adoption are facilitated by regulatory-processing needs, healthcare has stricter oversights. These contextual differences emphasize the significance of institutional alignment in Qatar (Alnuaimi et al., 2022).

Table 1. Comparison of Theoretical Framework

Framework	Strengths	Limitations	Relevance to Qatari Context
Technology Acceptance Model (TAM) (Davis, 1989)	Explains adoption behavior through perceived usefulness and ease of use; widely applied in technology diffusion research	Overemphasizes rational decision-making; neglects institutional and cultural factors; weak in uncertain contexts	Predicts intention for GenAI adoption but underestimates regulatory ambiguity, reputational risks, and cultural norms that strongly shape actual adoption in Qatar.
Resource- Based View (RBV) (Barney, 1991)	Positions GenAI as a strategic asset; emphasizes value, rarity, inimitability, and non-substitutability of resources	Assumes static, ownable resources; less suited to cloud-based AI services; under theorizes institutional assets such as legitimacy and regulation	Captures the value of Arabic culture, legitimacy, and trusted networks. However, in Qatar competitive advantage depends heavily on compliance, state endorsement, and cultural alignment – factors RBV treats only marginally.
Dynamic Capabilities (Teece et al., 1997; Teece, 2018)	Explain how firms' sense, seize, and reconfigure resources in fast-changing environments; highlights adaptability.	Presumes organizational slack, process maturity, and absorptive capacity often lacking in SMEs; overemphasises large firms' capabilities.	Useful for explaining how Qatari start-ups reconfigure processes under AI adoption. Yet SMEs often rely on state-driven initiatives and external vendors, limiting their ability to enact DC independently.
Experiential Learning Theory (Kolb, 1984)	Describes learning as iterative cycles (experience, reflection, conceptualization, experimentation); supports navigation of uncertainty.	Can appear overly individual-centric; underplays organizational codification and scaling of knowledge; may conflict with slower cultural norms of decision-making.	Reflects how Qatari entrepreneurs adopt GenAI through trial-and-error learning. Yet, GenAI's rapid tempo outpaces traditional consensus-driven processes, creating friction between cultural pace and technological speed.
Effectuation (Sarasvathy, 2001; Fisher, 2012)	Explains entrepreneurial action under uncertainty; emphasizes experimentation; leveraging networks, and affordable loss.	Can downplay institutional constraints; assumes flexibility in experimentation that may not hold in culturally or regulation-sensitive contexts.	Fits Qatar's relationship-oriented ecosystem where networks are key. However, the principle of "affordable loss" is constrained by high reputational and compliance risks.

Source: Authors' Own Work

As Table 1 shows, there is currently no single framework that reflects the multidimensional impact of GenAI adequately. An integrated framework of TAM (behavioral intention) RBV (strategic resources), Dynamic Capabilities (adaption), ELT (iterative learning) and Effectuation (bounded experimentation) is therefore needed in order to reflect Qatar's policy-driven and cultural embedded entrepreneurial environment. Table 2 presents the gaps identified in literature: limited empirical evidence on negative effects, methodological reliance on conceptual studies (Nambisan, 2017), underrepresentation of emerging economics (Cockburn et al., 2018) and theoretical fragmentation.

Table 2. Research Gaps identified in literature

Type of Gap	Existing Research Focus	Key Limitations	Implications in the Qatar/GCC context	References
Empirical	Studies emphasize benefits of GenAI (efficiency, innovation, competitive advantage)	Downsides such as ethical controversies, skill erosion, data dependence, and weak governance remain underexplored	Qatari start-ups face heightened risks around data governance, ethics and talent gaps; despite recognition, these remain under-investigated.	Dwivedi et al. (2023); Mittelstadt et al. (2016); Binns (2018)
Methodological	Dominated by conceptual/exploratory and case-based studies	Lack of large-scale quantitative studies to test causal and moderating factors	Qatar's entrepreneurial ecosystem requires robust empirical data to guide policy and practice in AI adoption.	Nambisan (2017)
Contextual	Research concentrated in developed economies	Neglects emerging markets with distinct institutional, regulatory, and socio-cultural dynamics	Qatar's QNV 2030 and AI strategy 2031 offer a unique-state driven innovation context, yet systematic empirical work is limited.	Cockburn et al. (2018); von Briel et al. (2018); Al-Kwifi et al. (2020); Alhumaidi et al. (2022).
Theoretical	Heavy reliance on TAM or RBV.	TAM neglects institutional/cultural dynamics; RBV assumes static resources; limited integration of ELT and Dynamic Capabilities.	Capturing GenAI adoption in Qatar requires a multidimensional framework integrating intention, resources, legitimacy, and adaptive learning.	Venkatesh and Bala (2008); Marangunic and Granic (2015); Wade and Hulland (2004); Bharadwaj (2000); Corbett (2005); Pittaway and Cope (2007); Warner and Wager (2019); Karimi and Walter (2015)

Source: Authors' own work

Drawing from the identified gaps and theoretical underpinnings, four testable hypotheses are formulated:

H1: Perceived benefits of GenAI positively predict its adoption among Qatari start-ups (Davis, 1989; Barney, 1991).
H2: Perceived barriers to GenAI implementation negatively predict its adoption among Qatari start-ups (Rogers, 2003).
H3: Ethical concerns negatively predict GenAI adoption among Qatari start-ups (Mittelstadt et al., 2016).
H4: Ambiguity moderates the relationship between ethical concerns and GenAI adoption, such that the negative effect of ethical concerns is stronger under conditions of higher ambiguity (Kolb, 1984; Teece, 2018).

These hypotheses provide a structured agenda to examine the multidimensional impact of GenAI adoption within Qatar's entrepreneurial system. This study makes an empirical contribution in terms of quantitative testing in the context of Qatar's start-up ecosystem, contextually as a way of adapting within GCC institutional realities, and theoretically in the form of multiple frameworks.

3. Methodology and Data Sources

This study explores the impact of Generative Artificial Intelligence (GenAI) on the entrepreneurial processes in the Qatari start-up ecosystem. The study's design is informed by the Research Onion Framework (Saunders et al., 2019), as illustrated in Figure 1. Within this framework, elements such as research philosophy, approach, design, strategy, time horizon, and analysis techniques are systematically structured to ensure overall coherence. The study has a positivist philosophy, assuming an objective external reality, which can be observed, measured and generalized through empirical testing (Creswell and Creswell, 2017). This is appropriate in light of the hypothesis-driven analysis of the relationships between the adoption of GenAI and entrepreneurial outcomes of the start-up ecosystem in Qatar. By using positivist logic, the study investigates the causal relationship, for example, if perceived usefulness is predictive of adoption behaviour (TAM) or if dynamic capabilities mediate innovation outcomes in a systematic, replicable and statistically verifiable manner. Established measurement instruments and statistical techniques were used to ensure that bias was minimized, and reliability and generalizability were ensured in the

Qatari context (Park et al., 2020). Alternative paradigms were not considered because the study's emphasis on quantitative hypothesis testing.

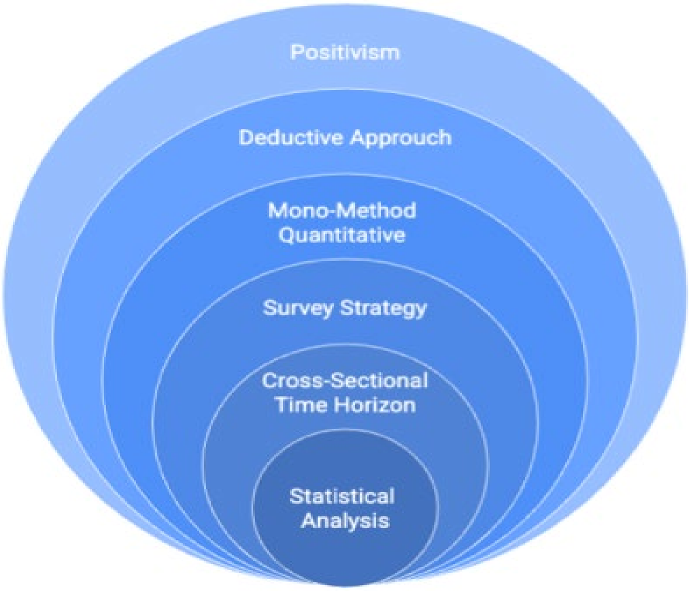


Figure 1. Research Methodology Structure

Drawing from perspectives such as TAM, RBV and Experiential Learning Theory, hypotheses were formulated and tested using survey data from Qatari start-ups. Deduction facilitates generalizable results and allows exploration of association between predefined variables (Bryman, 2016), beyond ensuring a theoretical foundation, to ensure situational relevance to Qatar Vision 2030 and National AI Strategy 2031. A mono-method quantitative design was adopted, using an online survey as the primary data collection instrument. This design enables the systematic comparison of organizations, industries, and stages of development and enables the use of multivariate statistical techniques, such as regression analysis and structural equation modeling (Hair et al., 2019; Lamm et al., 2020). The structured format enhances reliability and consistency, supporting hypothesis testing derived from TAM, RBV, and Enterprise Leadership Theory (ELT). The survey instrument was adapted from validated scales in the technology adoption and entrepreneurship literature to ensure validity and reliability. It consisted of 5 main sections: participants and start-up profile, GenAI adoption screening, usage and impact evaluation, barriers and challenges, and open feedback. Question types comprised of Likert scales and multiple-choice options to help conduct quantitative analysis.

Data was collected via Microsoft Forms. A multi-channel recruitment strategy was pursued in order to maximize reach and diversity while recruiting participants. Invitations were sent through LinkedIn posts, targeted e-mail campaigns, professional networks, co-working spaces, and industry event to maximize reach within Qatar's start-up ecosystem. Participation was voluntary, with informed consent obtained through mandatory digital confirmation. Data was analyzed using the statistical package software SPSS. Data screening, including handling missing values, outliers' identification, and checking of the assumptions of regression analysis (e.g., normality, linearity, homoscedasticity and multicollinearity) were carried out prior to the hypothesis testing in accordance with best practice (Field, 2018). Descriptive statistics and bivariate correlations were performed before regression analysis to investigate preliminary relationships between variables and check for possible multicollinearity. Multiple regression analysis was then used to test H1-H3 followed by moderation analysis for H4, which involved adding the interaction terms to determine the influence of the ethical concern and ambiguity on the strength and direction of the relationships. Five key theoretical constructs were operationalized using validated measurement scales adapted to the GenAI context. Table 3 presents the comprehensive mapping of constructs to survey items and theoretical foundations.

Table 3. Variable Operationalization

Construct/Variable	Survey Items (Q1 - Q19)	Theoretical Foundation	Measurement Scale	Linked Research Objectives	Linked Hypotheses
Participant and Start-Up Profile	Q1 - Q6 (role, sector, years in operation, firm size, employees)	Contextual/demographics	Categorical	Provides contextual sample profile	N/A
GenAI adoption	Q7 - Q11 (presence of adoption, type, duration, frequency, business functions)	TAM, RBV	Likert + Categorical	RO1: Examine adoption patterns across functions	H1, H2, H3: Perceived benefits, barriers, and ethical concerns predict adoption.
Perceived Usefulness and Ease of Use	Q12 (business improvement, efficiency, usefulness)	TAM	5-point Likert	RO3: Test adoption drivers	H1: Perceived benefits predict adoption
Ethical and Contextual Barriers	Q14 - Q15 (data privacy, regulation, ethics, infrastructure)	Extended TAM; Ethics in AI; RBV; Institutional theory	5-point Likert	RO4: Assesses ethical and contextual barriers	H2, H3, H4: Barriers and ethical concerns predict adoption; ambiguity moderates the ethics–adoption link
Exploratory Feedback	Q16 - Q19 (future expectations, reflection, learning, open comments)	ELT	Structures multiple choice + open text	Supports all research objectives	N/A

The target group comprised of founders and senior managers of start-ups operating in Qatar, as primary decision-makers regarding GenAI adoption. A purposive sampling technique was employed to recruit participants with direct experience with GenAI implementation (Patton, 2015). Stratification ensured representation of different technology, retail and services sectors. The target sample size of 100 respondents was established to ensure sufficient statistical power for multiple regression analysis (Hair et al., 2019). Power calculations indicated that approximately 85-90 participants were required to detect medium effect sizes (Cohen $f^2 = 0.15$) at $\alpha = 0.0$ with 80% power. A target of 100 gave a margin of data quality consideration but was still feasible within the start-up ecosystem in Qatar. The study was approved by the Research Ethics Committee and adhered to the GDPR guidelines. Participation was voluntary and informed consent obtained digitally. Data was anonymized, aggregate findings only are reported. All data were stored in password-protected system with secure authentication and will be retained and destroyed in accordance with institutional policy.

4. Results and Discussions

This section presents the empirical findings in relation to the four research objectives and hypotheses (H1–H4). A total of 106 valid survey responses were obtained from decision-makers across multiple industries, ensuring robust representation of Qatar's start-up ecosystem. Analyses were conducted using SPSS v29. Reliability and validity were established prior to hypothesis testing; Cronbach's α values exceeded the 0.70 threshold (Nunnally, 1978) and KMO values surpassing adequacy benchmarks (Kaiser, 1974). Descriptive statistics, Pearson's correlation, regression and moderation analyses were employed to test predictive and contextual effects. Technology-based firms constituted the largest group (n=43, 40.6%), followed by services (n=33, 31.1%) and retail (n=28, 26.4%). Health tech (n=1, 0.9%) and oil and gas construction (n=1, 0.9%). The distribution reflects a technology-dominant but diversified ecosystem, supporting cross-sectional analysis. Respondents occupied senior leadership roles: 47

leaders (44.3%), 31 founders/cofounders (29.2%), and 25 senior managers (23.6%). Employees, team leads, and directors constituted 2.8% (n=3), showing that findings reflect executive-level strategic perspective on GenAI implementation. Most firms had operated for 3-5 years (n=44, 41.5%), followed by 1-3 years (n=32, 30.2%). Firms operating more than 5 years accounted for 18.9% (n=20), while early-stage forms (<1 year) comprised 9.4% (n=10). The sample represents scaling-stage start-ups. Mid-sized start-ups dominated: 51-100 employees (n=47, 44.3%) and 21-50 employees (n=32, 30.2%). Smaller firms included 6-20 employees (n=12, 11.3%) and 1-5 employees (n=10, 9.4%), while 100+ employees represented 4.7% (n=5). The distribution indicates organizational capacity sufficient for technology integration. GenAI was mostly applied in idea generation (Mean = 3.46, SD = 0.615), customer engagement (Mean = 3.44, SD = 0.744), business planning (Mean = 3.29, SD = 0.766), scaling/growth (Mean = 3.23, SD = 0.763). Product development recorded the lowest mean (Mean = 3.14, SD=1.052), indicating greater variability. Adoption is strongest in the knowledge-intensive and strategic functions. Table 4 presents the summary statistics of the functional areas in which GenAI was applied.

Table 4. Summary statistics for functional areas

Functional Area	**N**	**Mean**	**Standard deviation**
Idea generation	80	3.46	0.615
Business planning	80	3.29	0.766
Scaling/growth	80	3.23	0.763
Product development	80	3.14	1.052
Customer Engagement	80	3.44	0.744

GenAI adoption was reported by 80 respondents (75.5%), while 26 (24.5%) were non-adopters. The high adoption rate reflects strong technological engagement within Qatar's start-up ecosystem. Among adopters (n=80), GenAI positively influenced idea generation (Mean = 3.49, SD = 0.729), competitive advantage (Mean = 3.39, SD = 0.771), decision-making (Mean = 3.38, SD = 0.753), business plan quality (Mean = 3.31, SD = 0.866), and scaling acceleration (Mean = 3.23, SD = 0.999). Cross-tabulation revealed no significant sectoral differences in adoption rates. These consistently positive innovation-related means address Research Objective 2, indicating that GenAI adoption is associated with improved innovation outputs, with idea generation and competitive advantage showing the strongest gains and scaling acceleration showing comparatively greater variability. These descriptive findings also address Research Objective 2 with respect to growth, indicating that GenAI adoption is associated with modest improvements in growth performance indicators, tempered by structural constraints reflected in the lower and more variable scaling mean. Cost emerged as the most significant barrier (Mean = 3.22, SD=0.768), followed by ethical concerns (Mean = 3.20, SD= 0.833). Internal resistance (Mean = 3.11, SD = 0.998), uncertain ROI (Mean = 3.10, SD =0.742), technical skills (Mean =3.05, SD= 0.695), data privacy (Mean = 3.03, SD= 0.762), and ambiguity (Mean =2.98, SD= 0.805) were moderate constraints. Overall, financial, ethical, and organizational factors represent primary implementation challenges.

The ANOVA test revealed significant sectoral differences for technical expertise requirements (F=2.972, p = 0.023), ethical concerns (F=2.761, p=0.032), and staff resistance (F=3.598, p = 0.009). Cost, data privacy, ROI, and ambiguity did not differ significantly across sectors. Findings suggest sector-specific variation in skills, governance pressures, and workforce adaptability. Table 5 presents the ANOVA test results.

Table 5. ANOVA Test results

	ANOVA	**Sum of Squares**	**Degree of freedom**	**Mean Square**	**F-statistic**
Technical Expertise	Between groups	5.346	4	1.336	2.972** (.023)
	Within groups	45.419	101	0.450	
	Total	50.764	105		
Cost	Between groups	3.469	4	0.867	1.496 (0.209)
	Within groups	58.540	101	0.580	
	Total	62.009	105		
Data Privacy	Between groups	1.873	4	0.468	0.801 (0.527)
	Within groups	59.042	101	0.585	
	Total	60.915	105		
Ethical Concerns	Between groups	7.179	4	1.795	2.761** (0.032)
	Within groups	65.660	101	0.650	
	Total	72.840	105		

ROI	Between groups	2.897	4	0.724	1.331 (0.264)
	Within groups	54.962	101	0.544	
	Total	57.858	105		
Ambiguity/Uncertainty	Between groups	2.881	4	0.720	1.118 (0.352)
	Within groups	65.081	101	0.644	
	Total	67.962	105		
Staff resistance	Between groups	13.050	4	3.263	3.598*** (0.009)
	Within groups	91.591	101	0.907	
	Total	104.642	105		

Note: *The values in parenthesis are the p-values of the F-statistic. ** and *** denote 5% and 1% significance levels.*

Cronbach's alpha demonstrated strong reliability: perceived benefits scale ($\alpha = .812$), and barriers scale reached ($\alpha = .805$). The KMO value (.575) exceeded the minimum threshold, and Bartlett's test of Sphericity was significant, $\chi^2(120) = 1078.33$, $p < .001$, confirming sampling adequacy and inter-item correlations. The measurement model is reliable and valid. Pearson correlations revealed a strong positive relationship between adoption and perceived benefit ($r = .72$, $p < 0.01$). Adoption showed weaker correlations with barriers ($r = .22$, $p < 0.01$) and ethical concerns ($r = –.066$, ns). Adoption correlated positively with competitive advantage ($r = .36$, $p < 0.01$). Perceived usefulness demonstrates the strongest association with adoption decisions. The correlation results are presented in Table 6.

Table 6. Correlation Matrix

	Adoption	**Perceived benefits**	**Barriers**	**Ethical Concerns**	**Competitive Advantage**
Adoption	1	0.721***	0.222**	-0.066	0.364***
Perceived benefits	0.721***	1	0.066	-0.018	0.607***
Barriers	0.222**	0.066	1	0.751***	-0.136
Ethical Concerns	-0.066	-0.018	0.751***	1	-0.087
Competitive Advantage	0.364***	0.607***	-0.136	-0.087	1

Note: *The asterisks ** and *** denote 5% and 1% significance levels.*

Regression and moderation analyses were performed to assess the predictive and contextual factors of GenAI adoption (RO4). A baseline multiple regression model was used to test the effects of perceived benefits, barriers and ethical concerns as predictors of adaptation. The model was statistically significant, $F(3, 102) = 40.64$, $p < .001$ with an explanatory power of R-squared = .62, which means that 62% of the variance in adoption was explained by the predictors. Perceived benefits were the best positive predictor (beta= .69, $t = 8.42$, $p < .001$, 95% CI [.53, .85]), which is consistent with the Technology Acceptance Model (Davis, 1989), which suggests that the usefulness of an innovation is the most important factor in determining if it will be adopted. Barriers had a significant negative influence (beta = -.44, $t = -5.13$, $p < .001$), which captures the constraints of resource limitations as well as complexity in the Diffusion of Innovation theory (Rogers, 2003). Ethical concerns also had a negative impact on adoption (beta = - .37, $t = - 4.76$, $p < .001$), which is consistent with Institutional Theory, which emphasizes the role of governance pressures and legitimacy considerations as inhibitors to entrepreneurial behaviour. In order to investigate conditional effects, a moderation effect analysis was conducted on the relationship between ethical concerns and ambiguity by using interaction terms. The extended model (Model 2) demonstrated greater explanatory power, $R^2 = .65$, $F (4, 101) = 34.77$, $p < .001$, highlighting the significance of contextual moderators. The interaction between ethical concerns and ambiguity was significant (beta = - .27, $t = - 2.65$, $p = .01$, $\eta^2 = 0.07$), meaning that in conditions of high ambiguity, ethical concerns have a greater negative effect on adoption. Although the effect of ambiguity was not direct (beta = .07, $p > .05$), its moderating effect shows that adoption decisions are especially sensitive to issues of socio-ethical legitimacy when the level of uncertainty is high. The regression results are presented in Table 7.

Table 7. Regression Results

Model	R	R-squared	Adjusted R-squared	F-statistic
1	0.785	0.616	0.601	40.684***
2	0.806	0.650	0.631	34.769***

*Note: **Dependent Variable: Adoption**. Independent Variables (**Model 1**): Constant, Ethical concerns, Perceived benefits, Barriers. Independent Variables (**Model 2**): Constant, Ethical concerns, Perceived benefits, Barriers, Ambiguity. The asterisks ** and *** denote 5% and 1% significance levels.*

These findings provide strong empirical support for H1-H3, confirming that perceived benefits are the primary driver of adoption while barriers and ethical concerns significantly constrain it. The moderation analysis further supports H4, showing that ambiguity intensifies the negative effect of ethical concerns on adoption, underscoring the contextual importance of legitimacy in shaping GenAI adoption within Qatar's entrepreneurial ecosystem. Table 8 compiles the outcomes of the hypothesis testing and links each hypothesis to the statistical analyses carried out, the results obtained, and the associated interpretations.

Table 8. Summary of Hypothesis Testing

Hypotheses	Evidence	Verdict	Interpretation
H1: Perceived benefits positively predict adoption	$\beta = .69$, $t = 8.42$, $p < .001$	Supported	Perceived usefulness is the dominant driver of adoption, consistent with TAM.
H2: Barriers negatively predict adoption	$\beta = -.44$, $t = -5.13$, $p < .001$	Supported	Cost, technical skill gaps, and integration complexity significantly suppress adoption.
H3: Ethical concerns negatively predict adoption	$\beta = -.37$, $t = -4.76$, $p < .001$	Supported	Governance and legitimacy concerns act as a meaningful brake on adoption.
H4: Ambiguity moderates the ethics–adoption link	Interaction $\beta = -.27$, $t = -2.65$, $p = .01$; direct effect of ambiguity ns ($\beta = .07$, $p > .05$)	Supported	Ethical concerns matter more when uncertainty is high; ambiguity alone does not deter adoption.

The first research objective focused on examining the adoption of GenAI by start-ups in Qatar and its effects on innovation. Perceived usefulness was identified as a primary predictor of adoption and ease of use was the secondary predictor, which is consistent with TAM (Davis, 1989) and the evidence from around the globe (Dwivedi et al., 2023; Venkatesh & Davis, 2000). In Qatar, both institutional readiness and cultural legitimacy are key factors influencing adoption, reflecting the nation's policy-driven approach to digital transformation strategies. Sectoral differences were apparent: technology and professional services had higher adoption for innovation-intensive activities while resource constraint firms had cautious adoption. This is consistent with RBV where innovation requires mobilization and reconfiguration of limited resources (Barney, 1991). In Qatar however, adoption is highly encouraged by state lead support through incubators, government-backed accelerators, and strategic initiatives in line with the Qatar National Vision 2030 and the National AI Strategy 2031 (MCIT, 2024). This suggests an extension of RBV, where institutional resources supplement firm-level limitations. Ethical considerations moderated adoption, as concerns about data privacy, bias, and reputational risk tempered the enthusiasm of entrepreneurs—especially in the context of ambiguous regulations. This finding highlights the need to extend TAM by incorporating socio-ethical legitimacy as a determinant in resource-rich but regulation-sensitive contexts. Experiential Learning Theory (Kolb, 1984) explains this process, as entrepreneurs engage in adaptive experimentation to balance innovation potential with risk. Regression analysis provided evidence for positive relationship between GenAI adoption and innovation output which confirmed the validity of Hypothesis 1, showing increased idea generation, accelerated innovation cycles, and creativity.

The second objective examined GenAI's growth outcomes. While adoption had a strong positive association with innovation (H1), the association with growth was modest (H2). GenAI supported idea generation, prototyping, and experimentation, which supports the RBV view of technology as a strategic asset (Barney, 1991) and Dynamic Capabilities framework (Teece et al., 1997), which highlights the importance of sensing opportunities and reconfiguring resources. Translation of innovation into measurable growth was not as robust as in the developed economies (Nambisan, 2017; Zhang et al., 2023) because of constraints in the structure of the ecosystem, limited domestic market size, emerging funding ecosystem and cautious regulation (Villegas-Mateos, 2023; Albous et al., 2025). Thus, although RBV predicts that GenAI should increase innovation and growth, institutional and market infrastructure mediates value realization, with innovation coming first. The third objective was to identify barriers and moderators. Key barriers included: high cost of integration, lack of technical expertise, regulatory ambiguity and ethical concerns. Talent, both in the area of AI and local market expertise was scarce, similar to broader challenges in the GCC area (Albous et al., 2025).

Moderation analysis showed ethical and regulatory uncertainty weakened adoption-outcomes links (H4). Concerns focused on data privacy, bias, AI-generated content and cultural fit especially in sensitive sectors (Mittelstadt et al., 2016; Binns, 2018). This is an extension of TAM, as it shows that adoption is affected by non-technical moderators. Experiential Learning Theory (ELT) contextualizes the cautious, trial-and-error adoption strategies observed, which contrast with the faster and bolder experimentation typical of Western ecosystems (Chalmers et al., 2021). Barriers therefore influence the speed and development of adoption as opposed to just blocking it. The fourth objective was to examine extant theories in explaining the adoption of GenAI in Qatar. Findings provide support for TAM's emphasis on usefulness (Davis, 1989) but show also that institutional trust and ethical legitimacy are important additions to the mix in the Qatari context. RBV (Barney, 1991) and Dynamic Capabilities (Teece et al., 1997) have provided an explanation for innovation and adaptability, but their explanatory capacity was limited by regulating and cultural dynamics. ELT (Kolb, 1984) elaborated incremental strategies of learning, tempered by a culture of consensus and the rapid change of GenAI (Pittaway and Cope, 2007).

5. Conclusions and Recommendations

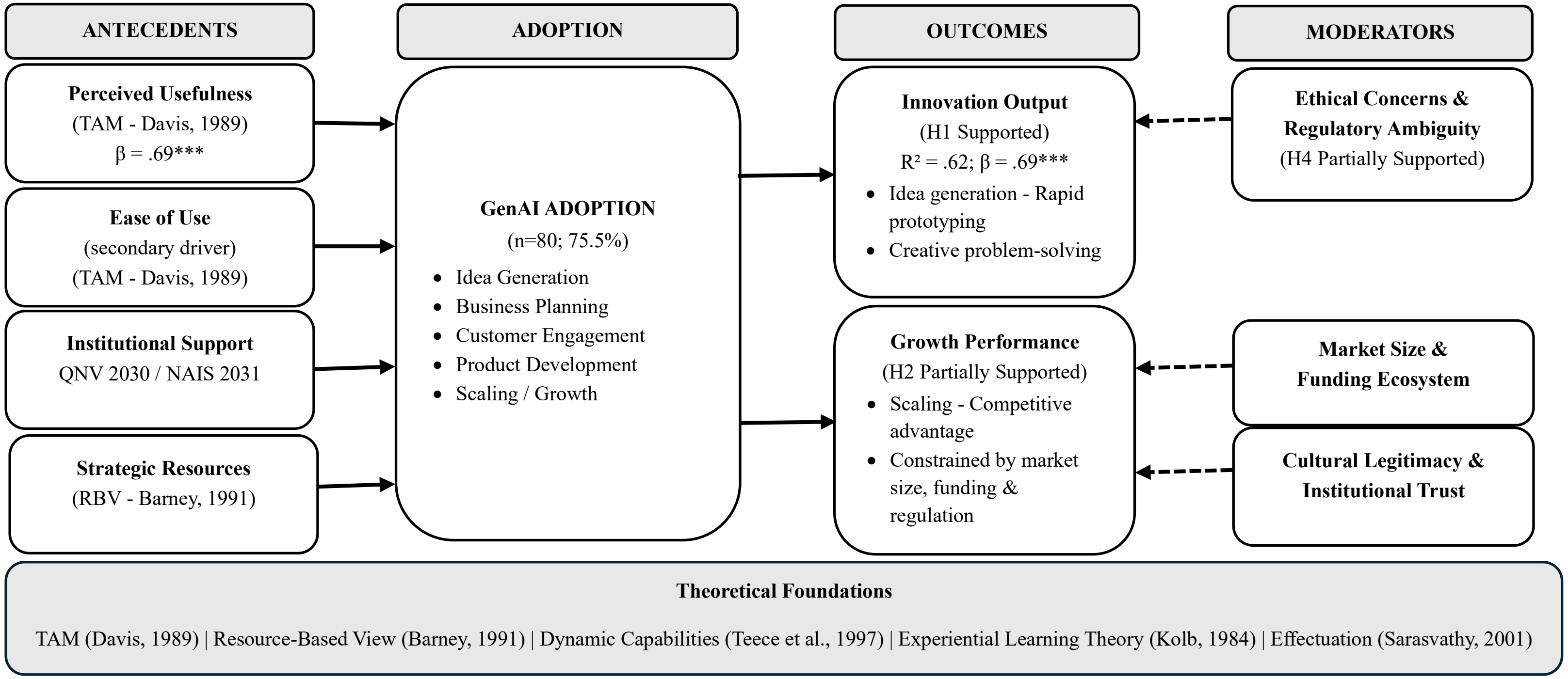
The study examined the role of GenAI in entrepreneurial processes in start-ups in Qatar and adopted a quantitative and positivist methodology to test hypotheses based on the Technology Acceptance Model (TAM), Resource-Based View (RBV), the Experiential Learning Theory (ELT), and the Dynamic Capabilities models. It probed hypotheses through a survey of 106 decision makers at start-ups, in order to offer insights on drivers of adoption, effects of innovation, barriers, and theoretical integration within a state-led ecosystem. The research focused on the scarcity of empirical research about the use of GenAI in emerging market start-ups. Four research objectives guided the investigation: mapping the patterns of adoption, assessing the effects of innovation and growth, determining the barriers and moderators, making significant contributions in three interrelated areas in the three domains, i.e., theoretical advancement, managerial practices, and policy development. By positioning GenAI in the context of QNV 2030, the findings fill important gaps in the academic literature and entrepreneurial practice in state-led ecosystem. Theoretically, integrating TAM, RBV, ELT, and Dynamic Capabilities demonstrates that perceived usefulness drives adoption, but ethical legitimacy and institutional trust are crucial moderators in emerging markets. The Resource-Based View (RBV) positions GenAI as a strategic resource (Barney, 1991), while Experiential Learning Theory (ELT) explains the role of iterative learning, and the Dynamic Capabilities framework (Teece et al., 1997) highlights adaptation through embedded routines.

From a managerial standpoint, the findings highlight that start-up should prioritize value communication over concerns about ease of use. Demonstrating tangible benefits—such as reduced time to market, enhanced customer engagement, and accelerated product development—is essential for driving adoption. The findings also underscore the value of phased implementation strategies, including pilot testing and controlled trials, which help organizations mitigate risks while customizing GenAI tools to sector-specific needs. Additionally, managers should adopt human-AI hybrid models, leveraging GenAI to augment rather than replace human creativity, and implement ethical safeguards to foster trust. At the policy level, the research advocates for a balanced approach to governance and innovation that supports technological advancement while upholding ethical standards. Strengthening data protection, reducing compliance-related bureaucracy, and developing culturally relevant AI ethics guidelines would contribute to a more trustworthy environment for adoption. Policymakers are also encouraged to invest in capacity building, especially through local talent development and organized knowledge transfer from global multinationals to local start-ups. These measures accelerate adoption and ensure that GenAI contributes directly to the national digital transformation agenda while remaining aligned with societal norms and values.

Although this study makes significant contributions, several limitations must be acknowledged. The purposive sampling strategy, with its focus on decision-makers such as founders, CEOs and senior managers, ensured informed response but carries potential selection bias and a lack of representativeness for other stakeholders, such as employees and customers, whose views may be different. The relatively small size of the entrepreneurial ecosystem of Qatar also limited representation. The cross-sectional design has another limitation in that it limits causal inference. While the results of regression and moderation analyses showed significant associations between variables, it is not possible to determine chronological order with these methods and the way in which the adoption behaviors develop over time. Additionally, the use of self-reported survey data opens the possibility of response bias, in particular optimism or social desirability, which may be heightened in Qatar's policy driven environment in which digital innovation is strongly endorsed. The geographic and institutional scope also contributes to the limitations in external validity: even though the research addresses a gap in understudied contexts of GCC, it may not be possible to directly apply findings to areas with different regulatory, cultural, or market conditions. Finally, the rapid evolution of GenAI means that there is a time limit to the results, as they are a snapshot and may easily become obsolete given the rate of technological development and policy creation.

Figure 2 presents an integrated framework synthesising the empirical findings of this study. The framework positions GenAI adoption as the central mechanism through which antecedent conditions translate into entrepreneurial outcomes within Qatar's start-up ecosystem. On the input side, perceived usefulness, operationalised in line with the Technology Acceptance Model (Davis, 1989) and confirmed as the dominant predictor ($\beta = .69$, $p < .001$), together with ease of use, institutional support through Qatar National Vision 2030 and the National AI Strategy 2031, and strategic firm-level resources consistent with the Resource-Based View (Barney, 1991), collectively drive the decision to adopt GenAI across five functional domains: idea generation, business planning, customer engagement, product development, and scaling. Adoption, in turn, exerts a strong and statistically significant positive effect on innovation output (H1 supported; $R^2 = .62$), including accelerated ideation, rapid prototyping, and creative problem-solving, while its relationship with growth performance is positive but more modest (H2 partially supported), reflecting structural constraints of the broader ecosystem such as limited market size, an emerging funding landscape, and evolving regulation. Three categories of contextual moderators, ethical concerns and regulatory ambiguity (H4 partially supported), market and funding conditions, and cultural legitimacy alongside institutional trust, attenuate the strength of the adoption-to-outcomes pathway, underscoring that GenAI's value realisation in an emerging, state-led economy is not automatic but is contingent on governance quality, socio-cultural alignment, and ecosystem maturity.

Figure 2. Integrated GenAI Adoption and Entrepreneurial Performance Framework



Source: Authors' own work

Theoretically, the framework integrates TAM, RBV, Dynamic Capabilities (Teece et al., 1997), Experiential Learning Theory (Kolb, 1984), and Effectuation (Sarasvathy, 2001), offering a holistic, context-sensitive lens that no single prior model provides alone. Practically, it signals that entrepreneurs should foreground the tangible strategic value of GenAI while simultaneously building ethical safeguards and adaptive routines, and that policymakers should address the moderating constraints, particularly regulatory clarity and trust-building infrastructure, to unlock the full growth potential that innovation-to-growth translation currently falls short of delivering.

This study opens a number of avenues for future research to further understanding GenAI adoption in entrepreneurial ecosystems. First, longitudinal research designs are recommended to trace the effects of GenAI adoption in terms of long-term impacts on innovation capacity, growth performance and organizational learning, especially as national policies and frameworks evolve. Second, cross-country comparative research that is conducted within the GCC itself, for instance, between Qatar, the UAE, and Saudi Arabia, could shed light on the impact of different regulatory and cultural contexts. Third, mixed methods approach that combine survey research with in-depth case studies would yield richer insights into the dynamics of decision-making processes, ethical dilemmas and the processes of organizational learning that are beyond the scope of what can be fully understood through quantitative data alone. Fourth, sector specific investigations are needed, especially for highly regulated and under researched sectors such as healthcare, finance and traditional services, where ethical issues and compliance pressures are most acute.

References

Al-Kwifi, O. S., Tien Khoa, T., Ongsakul, V., & Ahmed, Z. U. (2020). Determinants of female entrepreneurship success across Saudi Arabia. *Journal of Transnational Management, 25*(1), 3-29. https://doi.org/10.1080/15475778.2019.1682769

Albous, A., Hameed, S., & Alduaij, B. (2025). Generative AI and the future of work in the MENA region: A review of challenges and opportunities. *Journal of Business Research, 178,* Article 114407. https://doi.org/10.1016/j.jbusres.2024.114407

Alet, G. (2024). The perils of generative AI: Deskilling and the future of creative industries. *Journal of Business Venturing Insights, 21*, Article e00455. https://doi.org/10.1016/j.jbvi.2024.e00455

Ali, M., Al-Kwifi, O. S., & Al-Thawadi, H. A. (2024). The impact of AI on customer trust and engagement in the Gulf Region. *Journal of Business Research, 172*, Article 114300. https://doi.org/10.1016/j.jbusres.2023.114300

Alnuaimi, H., Al-Shami, S. A., & Al-Hajri, T. S. (2022). Digital transformation and entrepreneurship in the MENA region: A review of opportunities and challenges. *Journal of Business Research, 149*, 12–25. https://doi.org/10.1016/j.jbusres.2022.06.013

Alvarez, S. A., & Barney, J. B. (2007). Discovery and creation: Alternative theories of entrepreneurial action. *Strategic Entrepreneurship Journal, 1*(1–2), 11–26. https://doi.org/10.1002/sej.4

Amershi, S., Weld, D. S., Vorvoreanu, R., Fourney, B., Nushi, P., Collisson, P., Suh, J., Inkpen, K., & Ring, C. (2019). Guidelines for human-AI interaction. In Proceedings of the *2019 CHI Conference on Human Factors in Computing Systems (pp. 1-11). Association for Computing Machinery*. https://doi.org/10.1145/3290605.3300223

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99-120. https://doi.org/10.1177/014920639101700108

Bygrave, W.D. and Hofer, C.W. (1991) 'Theorizing about entrepreneurship', *Entrepreneurship Theory and Practice*, 16(2), pp. 13–22.

Bender, E. M., Gebru, T., McMillan-Major, A., & Mitchell, M. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency (pp. 615–628). Association for Computing Machinery*. https://doi.org/10.1145/3442188.3444458

Bennett, N., & Lemoine, G. J. (2014). What VUCA really means for you. *Harvard Business Review, 92*(1–2), 133–139.

Binns, R. (2018). The ethics of artificial intelligence: A systematic review. In A. I. G. I. O. A. I. The ethics of artificial intelligence: A systematic review. arXiv. *https://doi.org/10.48550/arXiv.1805.10118*

Bommasani, R., Hudson, D. A., & Agrawal, A. (2021). On the opportunities and risks of foundation models. arXiv. *https://doi.org/10.48550/arXiv.2108.07258*

Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company. *https://psycnet.apa.org/record/2014-07087-000*

Chalmers, D., Dwivedi, Y., Papadopoulos, T., & Williams, M. (2021). Innovation and entrepreneurship in the digital age: New challenges for theory and practice. *Journal of Business Research, 137*, 301-305. https://doi.org/10.1016/j.jbusres.2021.09.001

Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. *NBER Working Paper Series, No. 24449*. http://www.nber.org/papers/w24449

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., & Dwivedi, R. (2023). So, what exactly is ChatGPT? *International Journal of Information Management, 71*, Article 102646. https://doi.org/10.1016/j.ijinfomgt.2023.102646

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Sage Publications.

Gans, J., Goldfarb, A., & Tucker, C. (2019). The economics of artificial intelligence. *Journal of Economic Perspectives*, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Gartner, W. B. (1985). A conceptual framework for describing the entrepreneurial process. Academy of Management Review, 10(4), 696–706. https://doi.org/10.2307/258085

Gartner. (2024, January 10). Gartner Top 10 Strategic Technology Trends for 2024. *Gartner*. *https://www.gartner.com/en/articles/gartner-top-10-strategic-technologytrends-for-2024*

General Secretariat for Development Planning (GSDP). (2008). *Qatar National Vision 2030*. *https://www.diwan.gov.qa/about-qatar/qatar-national-vision-2030?sc_lang=en*

Gupta, M., & Yang, J. (2024). The rise of generative AI: A new era for technology adoption and human-AI collaboration. *Journal of Innovation & Knowledge, 9*(3), Article 100518. https://doi.org/10.1016/j.jik.2024.100518

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: The next big wave. *California Management Review, 61*(4), 5–24. https://doi.org/10.1177/0008125619854794

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kolb, D. A. (1984). Experiential learning: *Experience as the source of learning and development*. Prentice-Hall. https://www.researchgate.net/publication/235701029_Experiential_Learning_Experience_As_The_Source_Of_Learning_And_Development

Kusetogullari, A., Kusetogullari, H., Andersson, M., & Gorschek, T. (2025). GenAI in Entrepreneurship: a systematic review of generative artificial intelligence in entrepreneurship research: current issues and future directions. arXiv. *https://arxiv.org/abs/2505.05523*

Lamm, A. J., Lamm, K. W., & Carter, H. S. (2020). The importance of understanding survey methods to ensure the quality of data. *Journal of Agricultural Education, 61*(4), 1–13. https://doi.org/10.5032/jae.2020.04001

Li, J., Chen, X., & Zhang, Y. (2021). Digital entrepreneurship: A literature review and future research agenda. Journal of Business Research, 137, 306–318. https://doi.org/10.1016/j.jbusres.2021.09.002

Li, J., Wang, S., & Li, C. (2023). The role of artificial intelligence in customer relationship management: A review and research agenda. *Journal of Service Research, 26*(1), 3–20. https://doi.org/10.1177/10946705221088448

Mariani, M., & Dwivedi, Y. K. (2024). Generative Artificial Intelligence in Innovation Management: A Preview of Future Research Developments. *Journal of Business Research, 175*, Article 114542. https://doi.org/10.1016/j.jbusres.2024.114542

MCIT. (2024). Qatar National AI Strategy 2031. *https://www.mcit.gov.qa/en/artificialintelligence-committee/qatar-national-ai-strategy-2031*

Ministry of Communications and Information Technology (MCIT). (2024). GovAI Program for AI Innovation & Digital Transformation. *https://www.mcit.gov.qa/en/artificialintelligence-committee/govai-program/*

Mittelstadt, B., Allo, P., Taddeo, M., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society, 3*(2). https://doi.org/10.1177/2053951716679201

Nunnally, J. C. (1978). P*sychometric theory* (2nd ed.). McGraw-Hill.

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6), 1029-1055. https://doi.org/10.1177/1042258716688447

Park, Y., Kim, D., Cho, J., & Kim, M. (2020). The effects of perceived usefulness and ease of use on user acceptance of mobile learning. *International Journal of Mobile Learning and Organisation, 14*(4), 381–398. https://doi.org/10.1504/IJMLO.2020.109863

Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). Sage Publications.

Pittaway, L., & Cope, J. (2007). Entrepreneurship education: A literature review. *International Journal of Entrepreneurship and Innovation, 8*(3), 163–187. https://doi.org/10.5367/000000007781368817

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. *Academy of Management Review, 26*(2), 243–263. https://doi.org/10.2307/259121

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2019). *Research methods for business students* (8th ed.). Pearson.

Schumpeter, J. A. (1934). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle.* Harvard University Press.

Shane, S., Jr., & Venkataraman, S. (2000). The Promise of Entrepreneurship as a Field of Research. In Ed Roberts, *Academy of Management Review. 25(1).* 217–226. https://entrepreneurscommunicate.pbworks.com/f/Shane%2520%252B%2520Venkat%2520-%2520Ent%2520as%2520field.pdf

Singh, S., Aithal, A., & Gupta, A. (2024). Generative AI in business: A systematic review and future research agenda. *Journal of Business Research, 172,* Article 114407. https://doi.org/10.1016/j.jbusres.2023.114407

Statista. (2025). *Generative AI market size and user forecast in Qatar 2020–2031*. www.statista.com/outlook/tmo/artificial-intelligence/generative-ai/qatar

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://josephmahoney.web.illinois.edu/BA545_Fall%202022/Teece,%20Pisano%20and%20Shuen%20(1997).pdf

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40–49. https://doi.org/10.1016/j.lrp.2017.02.001

Venkatesh, V. and Davis, F.D. (2000) 'A theoretical extension of the technology acceptance model: four longitudinal field studies', *Management Science*, 46(2), pp. 186–204.

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Villegas-Mateos, M. (2023). The regulation of AI in the GCC: The case of Saudi Arabia and the United Arab Emirates. *Computer Law & Security Review, 50,* Article 105908. https://doi.org/10.1016/j.clsr.2023.105908

Von Briel, F., Davidsson, P., & Recker, J. (2018). Digital technologies as external enablers of new venture creation in the IT hardware sector. *Entrepreneurship Theory and Practice, 42*(1), 47-69. https://doi.org/10.1177/1042258717732779

Zahra, S. A. (2007). The two faces of international entrepreneurship: The role of international opportunities. In M. A. Hitt, M. T. Ireland, S. M. Camp, & D. L. Sexton (Eds.), *Strategic entrepreneurship: Creating a new mindset* (pp. 525–546). Blackwell Publishing.

Zhang, Y., Chen, X., & Luo, J. (2023). Generative AI and competitive advantage: Implications for digital entrepreneurship. *Journal of Business Research, 161*, Article 113123. https://doi.org/10.1016/j.jbusres.2023.113123