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Generative AI for business sustainability: Examining usability, usefulness, and triple bottom line impacts in small and medium enterprises

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ABSTRACT

Generative AI has emerged as a game-changing technology with great potential to enhance business sustainability. This study explores the adoption and application of generative AI among small and medium-sized enterprises (SMEs) in a small island developing state. The study utilizes the Technology Acceptance Model (TAM) and the Triple Bottom Line (TBL) framework. It integrates quantitative and qualitative methods to comprehensively understand generative AI's role in fostering sustainable business practices. Quantitative findings reveal that perceived ease of use and usefulness significantly influence SMEs' intentions to adopt generative AI, ultimately predicting its actual usage. Qualitative insights complement these findings by identifying four key applications: operational efficiency, data-driven decision-making, sustainable product and service innovation, and building a sustainable brand identity. Despite its potential, the study acknowledges limitations, including focusing on a single SIDS and relying on self-reported data, which constrain generalizability. However, these limitations do not diminish the study's importance, as it highlights practical pathways for SMEs to overcome resource constraints and achieve sustainability goals. The findings highlight the transformative role of generative AI in equipping SMEs with innovative tools to balance profitability with environmental and social responsibility. Policymakers are urged to support this transition through education and outreach, making generative AI accessible and practical for SMEs.

1. Introduction

The growing global challenges of climate change, resource depletion, and social inequality have intensified the need for businesses to adopt sustainable practices. While large multinational corporations have been the center of focus for enhancing sustainability [1], small and micro-sized enterprises (SMEs) are also critical players for our sustainable future [2]. However, recently, SMEs have been under increasing pressure to integrate efforts to preserve the environment and promote social welfare, seeking profitability and embracing the triple bottom line theory principles [3]. SMEs, which comprise the majority of enterprises globally [4–7], are uniquely positioned to contribute to sustainability due to their small size, which facilitates flexibility, innovation potential, and proximity to local communities [8–11]. However, these smaller businesses often face challenges, such as limited financial resources and intense competition from larger corporations [12–15]. These constraints can hinder SMEs' ability to fully embrace sustainability. To address this challenge, many SMEs are increasingly exploring using artificial intelligence (AI) as a solution [16,17]. However, there remains a significant gap in academic research focused on leveraging AI for enhancing sustainability within SMEs [1,18,19]

Artificial Intelligence has gained significant traction recently regarding its application in business settings [20–22]. Existing literature reported that it aids in optimizing supply chains [23–25], improving customer service [26–28], and enabling data-driven decision-making [29–31]. Among various categories of AI, generative AI represents a prevalent form. It consists of algorithmic models that create new content across various formats such as text, images, audio, and videos. It has gained widespread attention due to its accessibility and usefulness in personal and professional spheres [32]. Past scholars have noted the

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usefulness of large language models such as ChatGPT in various sectors such as education and marketing due to their ability to assist with research, provide virtual assistance, and facilitate decision-making [18]. The entrepreneurship literature showed that generative AI can help businesses automate routine tasks [33,34], enhance communication [35,36], provide real-time solutions to operational challenges [37,38], and aid in training and development [39].

Despite these advancements, significant research gaps make this area ripe for further inquiry. First, little is known about whether generative AI has been utilized to support business sustainability. While there is a growing body of literature on the application of AI in business, existing research tends to focus on two key areas: the collective use of all forms of AI and its implementation in large resource-rich firms for general management functions [1]. Although scholars have attempted to examine AI and sustainability in business, few studies have given dedicated attention to generative AI as a subset of AI. To the authors' knowledge, no study has bridged the gap in examining the usefulness of generative AI for sustainability functions across smaller enterprises.

Given the increasing pressure on businesses to adopt sustainable models [3], there is a need to explore how generative AI can be leveraged to enhance SMEs' environmental, social, and economic sustainability. This gap in the literature is further widened when considering the environments of SMEs in small island economies, which often operate under greater technological constraints than their counterparts in larger economies [13]. Past studies on generative AI have highlighted methodological limitations, as they often relied solely on quantitative or qualitative approaches. For these studies to have far-reaching implications, Abaddi [8] calls for the comprehensive integration of both approaches, such as mixed methods, to triangulate findings and gain deeper insights in this field. A third research gap pertains to the growing scholarly debate surrounding the potential harms of AI, suggesting that its impact may not always be beneficial. While some scholars argue that AI can significantly enhance productivity (Sipola et al. [40], others have raised concerns about its hidden carbon footprint due to the enormous energy demands of data centers [41] and the ethical implications, particularly related to data privacy and job displacement [42]. This lack of consensus reinforces the need for further research into the usefulness of generative AI in business sustainability.

To address these research gaps, we examine how user-friendliness and usefulness of generative AI may help usage adoption in SMEs through the perspectives of the Technology Acceptance Model (TAM). Furthermore, to better understand SMEs' user experiences with generative AI, we apply Triple Bottom Line (TBL) theory to examine how it has been utilized to support sustainability efforts. As such, this study is guided by the following research questions:

1. To what extent do perceived usefulness and ease of use of generative AI predict intentions to adopt and use it for business sustainability?
2. How does generative AI contribute to helping SMEs achieve business sustainability?

In answering these questions, we make three key contributions. First, we expand the discussion of the benefits of generative AI into the domains of sustainability and business. The extant literature shows that generative AI streamlines processes and analyzes complex data [1]. We show that its ease of use and usefulness constitute key elements of its adoption, and its use is tied to sustainability through enhanced operational efficiency, data-driven decision-making, product innovation, and brand identity. Second, by focusing on the context of a small island economy, we offer empirical evidence for regions that face unique disadvantages and are often overlooked in the global sustainability discourse. Finally, we provide practical implications for business owners, policymakers, and generative AI providers and recommendations on how AI tools can be integrated into sustainability strategies, particularly for SMEs.

In the remainder of the paper, we introduce the theoretical framework and develop our hypotheses. We then comprehensively describe our study's materials and methods. Next, we present the results, starting with the quantitative and then qualitative phases of data collection. This is followed by a dedicated discussion section encapsulating the study's implications for theory, policy, and practice. Finally, the article concludes with a summary and a section on limitations and future research directions.

2. Theoretical framework and hypotheses

2.1. Sustainability in business and SMEs

With growing concerns about climate change, businesses have been pressured to adopt sustainable practices within their daily operations [43,44]. Part of this demand comes from customers now seeking products and procedures that are environmentally and socially friendly and sustainable [45]. Over the years, the literature has documented sustainability as environmental protection, financial development, and social equality. From the lens of SMEs, they have been noted to have challenges with incorporating sustainability practices within their operations, which has led to increased competition from local and international markets [46]. In addition, SMEs face challenges with firm survival linked to sustainable growth [47]. Despite these challenges, SMEs contribute significantly to GDP and reduce unemployment; therefore, empirical research is needed to enhance sustainable development in these firms [7,48].

To fully understand how SMEs can contribute to sustainability, this study is anchored in the Triple Bottom Line (TBL) theory introduced by Elkington and Rowlands [49]. This sustainability framework emphasizes balancing economic, social, and environmental factors in business practices [50]. Using these three pillars, SME performance is driven by profitability and how responsibly they address people and the planet's needs, often called the 3Ps [7,50]. With the introduction of SME sustainability, key environmental benefits are waste reduction, clean technology use, and trash generation reduction. A few social benefits include a higher human standard of living, happiness, health, and life satisfaction [43]. Lastly, economic benefits include increased productivity and cost savings [51,52]. Without a doubt, SMEs are essential in addressing global challenges and should be assisted so they can accomplish this goal.

2.2. Generative AI in business: trends, applications, and challenges

Buchanan [53] describes artificial intelligence (AI) as the ability of computers to understand the nature of being intelligent. Dean et al. [54] states that AI is "the design and study of computer programs that behave intelligently." Within the SME, AI adoption refers to implementing, acquiring, using, and integrating AI systems in the business's operations [55]. Studies like Hansen and Bøgh [56] and Wei and Pardo [57] have identified AI technology within SME businesses as chatbots that support standardizations and the ability to generate content. In recent years, however, there has been an increase in the use of these AI technologies in large and small firms [58].

One such trend that has been increasing is using generative AI within the SME context to achieve business objectives. According to Pramod and Patil [59] generative AI is a subset of AI technology whose primary aim is to generate new content in text, images, original data, and other things. Within the business world, some of the primary uses of generative AI are the generation of prototypes, the analysis of trends, error detection, and assistance in decision-making [60,61]. Two common types of generative AI include ChatGPT and DALL-E, both designed by OpenAI. ChatGPT is a chatbot that uses AI technology to have human-like conversations, whereas DALL-E is a text-to-image software that allows users to generate images from prompts [62,63]. Regarding its usage and benefits, generative AI offers benefits to businesses and the ability to enhance their sustainability. AlQershi et al. [18] have identified a link between using generative AI, such as ChatGPT, and enhancements in sustainable business practices.

As mentioned in the previous section, the triple bottom-line theory highlights three pillars linked to sustainability: environmental, economic, and social [49]. With the growing popularity of generative AI, many businesses have been using it to enhance their business sustainability. Regarding the environmental pillar of sustainability, Generative AI allows businesses to understand ecological trends, such as air quality, pollution levels, and possible ways to reduce emissions from manufacturing [64]. Generative AI also allows better energy management through the maintenance and management of smart grids. There have also been enhancements in the supply chain process, leading to better logistics and reduced carbon footprint from transportation [65]. Generative AI usage also contributes to the societal pillar of sustainability by allowing businesses to achieve their corporate social responsibility. Companies can align their generative AI usage with the social development goals proposed by the United Nations to address inequality challenges through their policies [61]. Another main contribution of generative AI to business sustainability is its ability to assist in public and employee safety [66]. From the SME context, generative AI has reduced complex human administration tasks and increased customer satisfaction and loyalty [40].

Furthermore, generative AI significantly contributes to a business's economic sustainability pillar [67]. Generative AI offers cost-saving benefits by introducing automation tasks, which allow SMEs to increase their profits. Advertising using generative AI has also been identified as positively affecting SMEs in terms of cost savings and increased profits [67]. Generative AI has also been deemed a primary factor in helping SMEs expand into large firms.

While generative AI offers numerous opportunities and advantages to SME firms, it is also essential to acknowledge a few of the challenges associated with its usage. One of the main challenges is the likelihood of inaccurate information being generated. Balcıoğlu et al. [19] and Rudolph et al. [68] have identified that AI systems such as ChatGPT have produced incorrect information or "hallucinations." Another challenge of generative AI or technology, in general, is the high cost of investment needed. Tufféry [69] recognizes that the high initial investment cost may be challenging for SMEs to achieve. Lastly, the usage of generative AI has also been linked to questions about increases in unemployment due to the introduction of Artificial Intelligence Assistants [19]. However, despite these concerns, many businesses have transitioned to include some form of generative AI. AlQershi et al. [18] have identified that this has led to a growing gap in the literature, as little research is available on AI and business sustainability. Therefore, this study hopes to contribute to this gap in the literature by investigating the link between Generative AI and Sustainability business practices utilizing the TAM.

2.3. The Technology Acceptance Model (TAM) and SMEs

The Technology Acceptance Model (TAM) offers a theoretical background on adopting technology to understand user acceptance and utilization of generative AI in SMEs. The model focuses on perceived ease of use and usefulness, two critical components contributing to technology adoption [19]. Perceived ease of use is the degree of acceptance of new technology by someone who views technology as easy to use with little to no physical effort [70]. Perceived usefulness is the degree to which a person accepts that new technology would enhance their performance [70].

Studies within the SME context have used the TAM to understand perceived ease of use and usefulness in technology adoption [8,59]. SMEs face challenges when adopting AI, as it is perceived to be difficult to use [71]. However, as proposed by the TAM, SMEs have challenges implementing AI technologies due to a lack of knowledge and understanding [8,55]. Therefore, using the TAM and ensuring that ease of use is achieved can help increase the chances of AI adoption in SMEs [8]. In addition, Ahmed and Sur [72] also found that the TAM successfully understood AI adoption within the SME context. Ahmed and Sur [72] identified that ease of use, attitudes, and convenience were among the top factors affecting the adoption of AI in SMEs.

Some recent studies have used the TAM to understand and explore the acceptance of AI and technology within the SME context [8,55,59]. In a systematic review by Kelly et al. [73], the TAM was one of the leading technology acceptance frameworks used to understand the adoption of AI technologies. In addition, for exploring generative AI, Duong et al. [74–77] have used the TAM framework to explain the adoption of generative AI in various contexts. Within the SME context, studies such as Gupta [78–80] have used the TAM to explore AI and Generative AI Technology. In the following sections, the hypotheses for the study will be discussed.

2.4. Perceived usefulness and intention to use

According to Davis et al. [81], perceived usefulness is the degree to which someone views generative AI or technology to enhance their performance. Usefulness affects a person's attitude, behavior, and intentions toward new technology [8]. Within the SME context, perceived usefulness would be necessary to facilitate the adoption of generative AI since user expectations of how well AI can enhance their overall performance are needed. When Generative AI users see that systems such as ChatGPT have potential benefits that will improve their daily performance and productivity, their likelihood of adopting such systems becomes more likely [82]. In addition, Gupta [78] study found that perceived usefulness positively affects entrepreneurs' intention to use Generative AI. This effect is influenced by expected performance and effort from using AI Technology. The work of Tella and Olasina [83] also supports that TAM predicts that perceived usefulness affects a person's intention to use technology. Therefore, TAM suggests that if users of Generative AI believe it is a helpful tool, they will be more likely to utilize the AI technology [84]. More importantly, generative AI can enhance business sustainability through cost and time-saving strategies [85]. Therefore, to be competitive and sustainable, SMEs must adopt technology enhancements to ensure success [86]. Hence, based on the above arguments, the following hypothesis is proposed:

H1. *The perceived usefulness of generative AI positively and significantly influences the intention to use it to enhance sustainability in business practices.*

2.5. Perceived ease of use and intentions to use

Perceived ease of use is the second primary determinant of the TAM proposed by Davis et al. [81]. This determinant looks at the degree to which someone views technology adoption as easy and with little to no challenges [87]. Within the work of Tella and Olasina [83], technology perceived as easy to use by users has high intentions to use such technologies. Maheshwari [76] also found that the perceived ease of use of generative AI, such as ChatGPT, resulted in users' intentions to use the AI system within the classroom setting. This positive relationship between perceived ease of use and intention to use generative AI can further be explained by Nguyen et al. [88], where they suggested that users of generative AI can have the intention to use the AI system in the future since AI chatbots offer users prompts and commands that can make usage easier. AI systems such as ChatGPT have been known to be user-friendly and easy to use, which can contribute to users' willingness to use such systems in their businesses [89]. Within the SME context, it was also found that perceived ease of use was directly related to intention to use since generative AI offered users features that make it easy to use [90]. Therefore, based on the above arguments, the following hypothesis is proposed:

H2. *Perceived ease of use of generative AI positively influences the intention to use it for sustainability purposes in business.*

2.6. Perceived ease of use and perceived usefulness

Davis et al. [81] suggests that for technology to be adopted, it is essential for users to view it as applicable. However, although a user may view technological software as valuable, they may also see it as challenging, resulting in hesitation to adopt the technology. Therefore, based on the TAM, perceived ease of use is directly related to perceived usefulness [81]. Human beings, in general, prefer things and situations that are easy. Therefore, a preference for things that are easy to use is natural [91]. In practice and within the SME context, perceived ease of use has been tested and found to have a direct relationship with perceived usefulness [92]. Furthermore, Herzallah AT and Mukhtar [93] study on perceived ease of use and usefulness of technology in SMEs also highlighted the importance of the relationships mentioned above. Therefore, based on the above arguments, the following hypothesis is proposed:

H3. *Perceived ease of use of generative AI positively influences its perceived usefulness in achieving business sustainability goals.*

2.7. Intention to use and actual usage

Building on Jang [94] and Venkatesh et al. [95] definitions, intention to use generative AI is the degree to which someone intends to use generative AI systems such as ChatGPT within a business context, which results in outcomes like enhanced sustainability practices. For users to engage in a specific behavior, such as actual usage of Generative AI, they must first have the behavioral intention to do so [96]. In addition, other studies have also identified a link between intention to use and actual usage among technology users [97–99]. However, within the SME context and regarding the use of generative AI for sustainability practices, there is a link between intended use and actual usage [100]. During times of crisis, if entrepreneurs do not fully intend to use Generative AI to address business challenges, they will not use the generative AI systems. Furthermore, Panigrahi et al. [17] found that SMEs that used Generative AI Systems for sustainability practices after having intentions to use them. Therefore, based on the above arguments, the following hypothesis is proposed:

H4. *Intention to use generative AI for sustainability practices positively influences usage in business operations.*

Based on the theoretical constructs and the proposed relationships, Fig. 1 illustrates the conceptual framework that directs this study.

3. Materials and methods

3.1. Study design

The research has two primary objectives: (a) to investigate whether the acceptance of generative AI for business sustainability can be explained by the dimensions of the TAM model, namely perceived usefulness and ease of use, and (b) contingent on the validation of these initial relationships, to extend this inquiry by exploring how generative AI has explicitly been applied to achieve business sustainability.

To achieve these objectives, we adopted a sequential explanatory mixed methods design, comprising two phases: the collection and analysis of quantitative data and the gathering and analysis of qualitative data [101]. This is graphically presented in Fig. 2, accompanied by an explanation of the procedures involved in each phase.

3.1.1. Phase 1 - quantitative component

3.1.1.1. Sampling and recruitment. This study occurred in Trinidad and Tobago, a twin-island country in the Caribbean region. Notwithstanding the call for greater contextualization of entrepreneurship research Zahra et al. [103], Trinidad and Tobago provides a compelling context for this study as a country heavily reliant on its oil and gas sector, where sustainability practices are central to government policy. Despite its oil wealth, the SME sector plays a vital role in the nation's economic development, highlighting the importance of understanding how these businesses contribute to sustainability efforts [13]. To qualify for this study, participants must be SME business owners in Trinidad and Tobago who have implemented generative AI and adopted sustainable business practices. Since the exact sampling frame is unknown, sample size determination was guided by the requirements of the statistical analysis method employed. For Partial Least Squares Structural Equation Modeling (PLS-SEM), which is discussed in the results section, the recommended minimum sample size is ten times the number of observed variables [104]. With 17 observed variables in this study (detailed in the Instrumentation section), the required sample size is 170 participants.

To achieve this sample, purposive sampling was employed, targeting sustainable SME business owners through the authors' networks, including connections with business chambers, and disseminating invitations via social media platforms. Purposive sampling allows for selecting participants based on unique characteristics that align with our study's objectives. Our recruitment efforts yielded a total of 310 respondents, surpassing the minimum sample criteria, comprising 164 males (52.9 %) and 146 females (47.1 %) with a mean age of 37.25 years (standard deviation = 10.406).

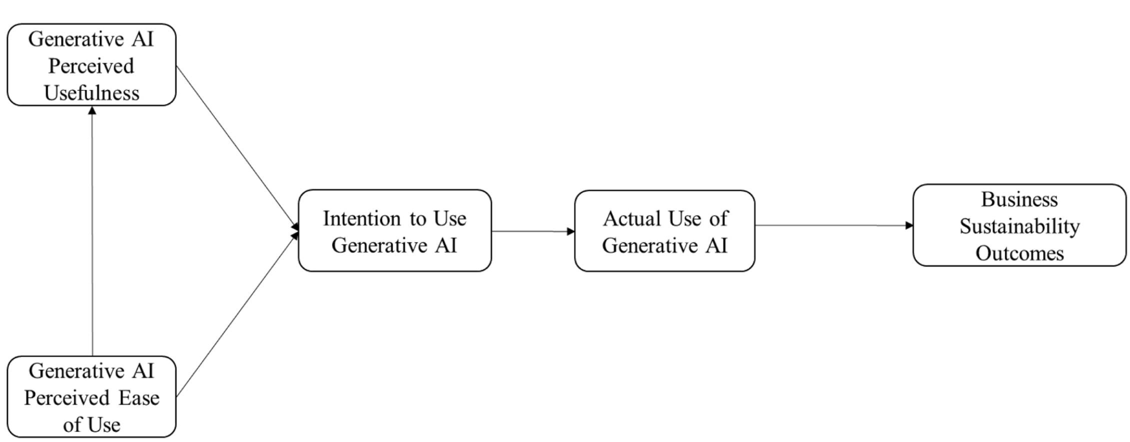

Fig. 1. Conceptual framework.
Source: Authors' adaptation of Davis et al. [81].

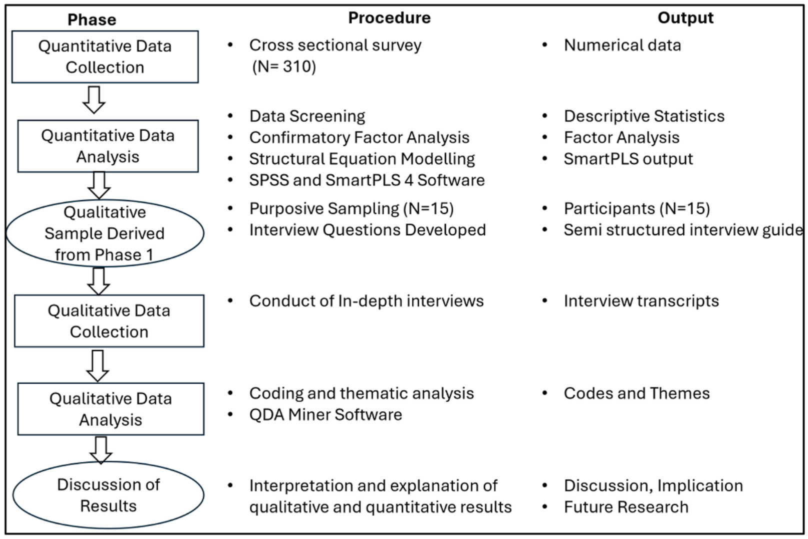

Fig. 2. Study design procedures adapted from Acquah et al. [102].

3.1.1.2. Data collection instrument. The survey instrument comprised three sections. The first section contained eligibility questions to confirm that respondents met the criteria following our initial screening. They were asked simple yes/no questions regarding their use of generative AI, their status as a SME, and their implementation of sustainable practices in their business. The second section included 17 items across four constructs: perceived usefulness, perceived ease of use, intentions to use, and actual usage, adapted from validated scales by Davis [81]. Each construct was measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). For example, perceived usefulness was assessed with statements like, “Using generative AI enhances my ability to implement sustainable practices in my business,” while ease of use was gauged with, “I find generative AI applications user-friendly.” Intentions to use generative AI were measured with statements such as, “I intend to continue using generative AI for enhancing sustainability in my firm,” and actual usage was assessed through statements like, “I have integrated generative AI into my daily operations to foster sustainability.” The third section included demographic questions on gender, age, and the highest level of education attained.

Prior to finalizing the instrument, two subject matter experts reviewed it for face validity, ensuring clarity, relevance, and alignment with research objectives. A pilot study with 19 SMEs led to minor refinements for clarity. Invitations, including study details and consent requests, were sent via email and WhatsApp. Depending on participants’ preferences, both online (via Google Forms) and printed methods were used for the survey.

3.1.1.3. Data analysis. Data was analyzed using SPSS (version 28) and SmartPLS Version (4.1.0.0). Normality tests such as kurtosis, skewness, Kolmogorov-Smirnov test, and Shapiro-Wilk test were conducted to assess the normality. Partial least squares structural equation modeling was used to analyze the proposed research model. Initially, the constructs were for reliability, convergent, and discriminant validity. Finally, the structural paths were tested using bootstrapping.

3.1.2. Phase 2 - qualitative component

While the quantitative component collected data to identify “*what*” relationships exist between perceived ease of use, perceived usefulness, intentions, and actual usage of generative AI for business sustainability using the TAM framework, we conducted semi-structured, in-depth interviews to gather qualitative insights on “*how*” participants utilized generative AI for sustainability purposes. Since our study aims to explore SME AI users’ experiences and gain deeper insights into the issues, we employed a phenomenological design, as it is the recommended approach for exploring experiences surrounding a particular phenomenon. This approach allowed participants to elaborate on their experiences, providing a richer understanding of the issues being studied [105].

3.1.2.1. Interview guide. The interview questions were developed based on a review of literature on triple bottom line theory, the use of generative AI in business, and consultations with two subject matter experts. Finalization of the interview guide was deferred until after the results of the first research phase were analyzed [106]. Sample questions included: “In what ways does your business utilize generative AI?”, “Can you elaborate on your reasons for incorporating it?”, “Has generative AI contributed to making your business more sustainable? If so, can you provide examples?" and “Do you believe generative AI has impacted your business profitability? How?” To ensure clarity, the guide was field tested with two participants, resulting in minor revisions for better comprehension.

3.1.2.2. Data collection. Due to participants’ preferences, we conducted the interviews using a combination of video conferencing (four participants) and face-to-face interviews (eleven participants). Interviews ranged from 25 to 60 min, and all sessions were recorded and transcribed verbatim. Quality checks were conducted by cross-referencing the transcripts with the recordings to ensure accuracy. Identifiable information was anonymized to maintain confidentiality, and transcripts were shared with participants to verify and validate their responses.

3.1.2.3. Sampling and recruitment. A purposive sampling strategy was employed to identify information-rich cases aligned with the study’s second objective. Participants from the initial pool of 310 respondents in Phase 1 were invited to participate if they met the following criteria: (a) utilized generative AI in their business at least twice weekly, (b) had been using generative AI for a minimum of two years, and (3) expressed willingness to participate in the interviews. A priori, a sample size of 25 was determined, consistent with the recommendation of 3–25 participants for a phenomenological study [105]. However, data collection ceased after 15 interviews, as saturation was achieved at this point [106], which is expected given the homogeneity of the group [107].

3.1.2.4. Data analysis and rigor. Thematic analysis was conducted using QDA Miner software, adhering to the procedures outlined by Braun and Clarke [108]. Transcripts were read iteratively to develop an in-depth understanding of participants' perspectives. Meaningful text segments were coded inductively, with new codes applied consistently across previously analyzed transcripts. Codes were aggregated into broader themes, capturing how generative AI enhances business sustainability.

To ensure the reliability and credibility of our findings, we conducted respondent validation by sharing summaries of findings with participants to confirm the accuracy of interpretations. To ensure inter-coder reliability, we independently coded the data before comparing results. Additionally, an external audit by an independent researcher verified the alignment of codes and themes with the data. We also cross-checked emerging themes against existing literature to confirm their validity.

3.1.3. Research ethics

Our university's institutional review board approved both phases of this study, with reference numbers CREC-SQ.2700/05/2024 for the quantitative phase and CREC-SA.2744/06/2024 for the qualitative phase. Participant consent was secured before data collection began. To protect anonymity and confidentiality, no identifiable information was recorded during the data collection process.

4. Results

4.1. Quantitative results

In this section, results are presented to address the study's first objective: to test hypotheses linking ease of use, usefulness, intentions, and generative AI usage for business sustainability.

4.1.1. Structural equation modeling

Partial least squares structural equation modeling (PLS-SEM) has been a widely used to test and validate theories. The present study adopted PLS-SEM because it does not have restrictions on the sample size and data normality [104]. The Kolmogorov-Smirnov and Shapiro-Wilk tests revealed that our data did not follow a normal distribution. Hence, PLS-SEM was preferable. A weighted path scheme using SmartPLS 4 (Version 4.1.0.0), adopting the standard initial weights of 2000 iterations, was used to estimate the proposed model. Moreover, bootstrapping with 5000 samples was applied to test the statistical significance of the PLS-SEM outcomes. Reflectively specified constructs were first analyzed for reliability and convergent and discriminant validity. An item's factor loading above 0.7 indicates that the construct accounts for more than 50 % of the variance in that item, suggesting an acceptable level of item reliability. Composite reliability (CR) and Cronbach's alpha provide the standard criterion for establishing construct reliability, where values between 0.7 and 0.95 suggest acceptable internal reliability of the constructs [104]. The convergent validity of the constructs is established using the average variance extracted (AVE) of all items linked to a specific trait, and an AVE above 0.5 indicates the convergent validity of the construct [109]. The results of the measurement model, i.e., factor loadings, composite reliability, Cronbach Table 1 and Fig. 3 give alpha, and average variance extracted (AVE). These results indicate that our measurement model has acceptable reliability and convergent validity.

The Fornell-Larcker criterion [110] and heterotrait–monotrait ratio of correlations (HTMT) [111] were used to assess the discriminant validity of the constructs. Table 2 shows that the under-roots of all the constructs are less than their correlations with other constructs, thus establishing discriminant validity. Additionally, an HTMT threshold of 0.90 is recommended to establish discriminant validity when constructs are conceptually similar, while 0.85 is recommended when constructs are distinct.

Table 3 indicates that the HTMT values of all constructs are below the recommended threshold of 0.85. Lastly, variance inflation factors (VIF) were checked to assess the potential multicollinearity issues. The VIF values for all the observed variables were below the threshold of 3 [112], indicating no multicollinearity issues.

Table 1
Reliability and convergent validity of the constructs.

Constructs	Items	Loadings	α	CR	AVE
Perceived ease of use	PEU1	0.770	0.893	0.905	0.650
	PEU2	0.772			
	PEU3	0.829			
	PEU4	0.830			
	PEU5	0.772			
	PEU6	0.861			
Perceived usefulness	PU1	0.806	0.851	0.855	0.627
	PU2	0.797			
	PU3	0.839			
	PU4	0.774			
	PU5	0.740			
Intention to use	IU1	0.887	0.881	0.864	0.782
	IU2	0.869			
	IU3	0.897			
Actual use	AU1	0.863	0.764	0.779	0.678
	AU2	0.797			
	AU3	0.863			

Following the measurement model, the structural model was assessed for hypothesis testing. Table 4 and Fig. 4 present the results of the hypothesis testing. The effect of perceived ease of use on perceived usefulness is positive and highly statistically significant ($\beta = 0.578$, $p < 0.001$). Moreover, the effects of perceived ease of use and usefulness on intentions to use AI are also significant ($\beta = 0.386$, $p < 0.001$; $\beta = 0.461$, $p < 0.001$). Lastly, the effect of the intention to use AI on the actual use of AI is also significant ($\beta = 0.533$, $p < 0.001$). As such, all hypotheses were supported.

4.2. Qualitative results

With all hypotheses supported, confirming the TAM framework for SMEs using generative AI for sustainability, the findings presented in this section expand on their lived experiences, addressing objective 2: exploring how generative AI is used for business sustainability

4.2.1. Participants characteristics

The sample consisted of fifteen participants, comprising eight males (53 %) and seven females (47 %). Most participants, 73 %, were aged 35 years and older, while 27 % fell within the 25–34 age range. Educationally, there was an even distribution, with 50 % holding a bachelor's degree and the other half completing secondary school. In terms of business classification, 33.3 % ($n = 4$) of the businesses were in the food and beverage sector, 33.3 % ($n = 4$) were in services, 25.0 % ($n = 3$) were in Agri-processing, 16.7 % ($n = 2$) were in manufacturing, and 16.7 % ($n = 2$) were in retail.

Table 5 summarizes the themes and codes relating to generative AI-enhanced business sustainability.

Theme 1. *Operational efficiency*

Firstly, operational efficiency emerged as a pivotal theme in the qualitative results, illustrating how generative AI optimizes business operations by maximizing output while minimizing inputs such as labor and finance. Most participants expressed that Generative AI significantly boosts labor productivity by automating routine tasks. Many reported utilizing AI as virtual assistants for managing emails, organizing orders, and generating reports. As one participant described,

> *"It frees up valuable time that I can redirect to sustainability projects". P10*

Another participant shared,

> *" I see it encourages greater employee engagement in community initiatives through making tasks like organizing workshops a breeze". P12*

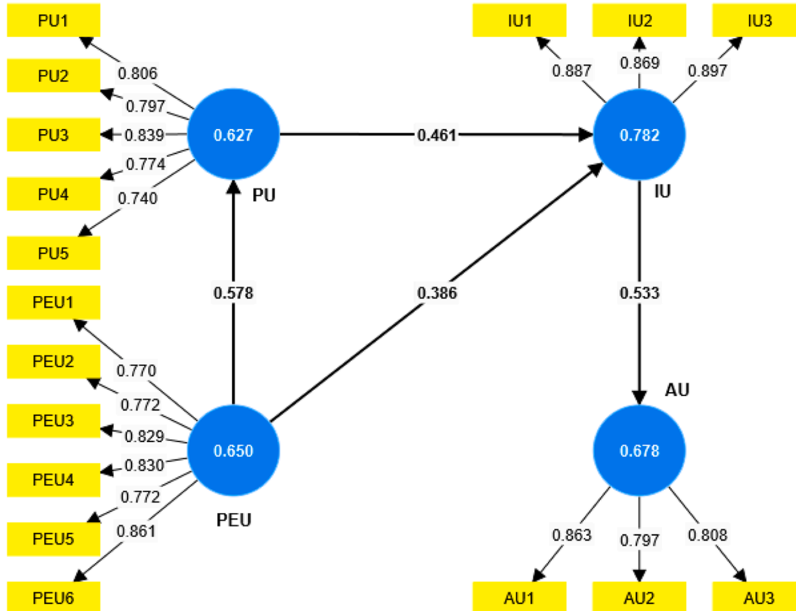

Fig. 3. Measurement model.

Table 2
Fornell Larcker's criterion of discriminant validity.

	AU	IU	PEU	PU
AU	**0.823**			
IU	0.533	**0.884**		
PEU	0.438	0.653	**0.807**	
PU	0.544	0.684	0.578	**0.792**

Note: AU = Actual use, IU = Intention to use, PEU = Perceived ease of use, PU = Perceived usefulness.

Table 3
HTMT values.

	AU	IU	PEU	PU
AU				
IU	0.649			
PEU	0.519	0.73		
PU	0.671	0.796	0.651	

Table 4
Path coefficients.

Relationships	β	Sample mean	Std. Deviation	t-statistic	p-values
PEU→PU	0.578	0.58	0.043	13.388	0.000
PEU→IU	0.386	0.386	0.049	7.823	0.000
PU →IU	0.461	0.461	0.049	9.363	0.000
IU→AU	0.533	0.535	0.053	10.025	0.000

Other participants described their experiences achieving social sustainability by using generative AI. For example, one owner highlighted how they fostered a culture of sustainability by generating bulletins to educate staff on their sustainability vision. Another participant remarked,

> *"It really lessens the time I spend behind a computer screen and reduces the burden on my office assistant which improves our physical and mental health" P13*

Participants also talked about the cost savings they enjoyed by using generative AI. It enables them to practice business sustainability without the need for costly experts. As one participant put it,

> *"I use it to translate work specs for my Venezuelan staff, without paying a translator. Now, I can hire those who feel hopeless." P6*

Some participants used it to analyze expenses and to identify cost-cutting opportunities. As described by a participant,

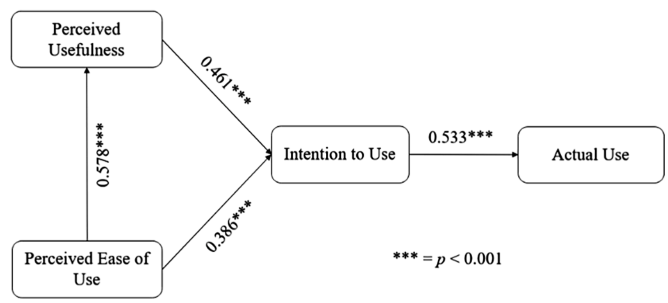

Fig. 4. Bootstrapped structural model.

Table 5
Themes and codes representing generative AI's usage in business sustainability.

Operational efficiency	• Enhanced labor productivity • Saves cost
Data driven decision making for sustainability	• Better scenario comparisons for sustainability • Demand forecasting for sustainability • Resource optimization
Sustainable product and service innovation	• Idea generation • Research and development
Building a sustainable brand identity	• Brand communication consistency • Creating a sustainable entrepreneur image • Engaging content tailored towards sustainability
Limitations of generative AI for sustainability	• Erosion of huma skills • Security concerns, • Stigma • Unreliable information

> *"When I saw how much I spent on gas, I use more Whatsapp now to meet clients which not only saves money but also reduces my company carbon footprint." P8*

All participants agreed that these efficiencies have increased profitability, allowing for greater investment in environmental and social initiatives.

Theme 2. ***Data-driven Decision Making for Sustainability***

Another recurring theme among participants was the role of generative AI in supporting sustainability-focused decision-making through data generation and analysis. All participants agreed that generative AI facilitated smarter choices that optimized resources, improved green choice evaluation, and forecasted demand for green products, thereby promoting sustainable business practices. As described by four participants

> *"I use it alongside my smart apps to monitor energy consumption. This helps me to conserve energy." P9*

> *"It has significantly improved our ability to identify green suppliers by analyzing potential partners far more efficiently than manual searches." P8*

> *"I don't feel guilty anymore. I just upload the CVs and it identifies applicants who seem a good fit for our sustainability like volunteerism or who have environmental management." P15*

> *"My assistant copy and paste customer feedback from online so we can see what people say about our eco-soaps, like if they like the smell or something so we know which ones to push"P14*

Theme 3. ***Sustainable product and service innovation***

Another key theme that emerged is sustainable product and service innovation. This theme highlights how generative AI was leveraged to generate innovative ideas for new products and improve existing processes aimed at enhancing sustainability. It encompasses the application of generative AI in idea generation and research and development, prioritizing social and environmental responsibility. Nearly all explicitly said they use it to brainstorm new product ideas or eco-friendly alternatives to their current product line. One participant revealed that it introduced him to the concept of circular economy, which sparked his success in transforming waste into a valuable product, boosting revenue. As he describes,

> *" Years I throwing away chicken heads and I always wondered what else it can be used for. My son use AI and it said I can make pet food and he also identified the grinders to process it. Now I am producing affordable fresh pet food as a byproduct. Its a lot cheaper than dog chow. Poor people in my community affords it, their dogs are well fed and I make money. Everyone wins." P6*

Some noted its use for designing visuals for sustainable product prototyping which speeds up their idea to market timeline whereas all participants utilized generative AI extensively to support research and development leading to sustainable business model innovation for some

Theme 4. ***Building a Sustainability Brand Identity***

Building a sustainable brand identity was a key theme highlighting how generative AI enhanced business sustainability practices. Participants noted that AI helped create engaging, tailored content to showcase their green identity. According to one participant,

> *"With just a few prompts, we create professional grade videos that clearly captures our sustainability agenda." P10*

Others maintained consistent messaging across social media for engaging posts. One participant credited it for crafting an excellent application and facilitating outreach content for workshops, increasing visibility. They noted,

> *" …and so, I won an award in the Green Entrepreneur category." P1*

Several participants utilized AI to design flyers, logos, and marketing materials, reinforcing their sustainable brand.

Theme 5. ***Limitations of Generative AI for Sustainability***

This theme highlights business owners' skepticism about using generative AI for sustainability. Concerns included security risks, with one participant noting,

> *"Uploading your information does not guarantee that competitors won't access it." P3*

There was also a stigma around using AI; some feared it would make them seem less technical. Ethical dilemmas arose regarding authenticity, with one respondent questioning,

> *"If it generates something on my behalf, is it truthful to claim I said it?" P2*

Additionally, some participants worried that over-reliance on AI could erode human skills and creativity, impacting staff morale. Reliability issues were also raised, such as misinformation and a lack of emotional intelligence in AI-generated content.

5. Discussion

The quantitative results provide significant insights into how perceived ease of use (PEU) and perceived usefulness (PU) of generative AI influence its adoption among SME business owners to enhance sustainable practices. Using PLS-SEM, the analysis revealed robust support for the proposed technology acceptance model [81], with all hypotheses being validated. These findings are discussed below, further enriched by the results of the qualitative component of our study.

5.1. Integrating model findings: generative AI usefulness

While numerous technologies continue to emerge at an alarming rate especially within e-commerce [113]; not all have proven to be effective calling for greater scrutiny of their utility [42,114]. However, our quantitative data found that PU and PEU were positively associated with intentions to use generative AI, which in turn predicted actual usage. This finding reinforces the broader applicability of TAM to emerging technologies, particularly in business settings. Notably, the positive relationship between PEU and PU suggests that SMEs find generative AI a good fit for their learning curve and valuable for addressing sustainability needs. Furthermore, PU substantially affected AI adoption intentions more than PEU. Interestingly, this was the same case found in prior studies, such as Abaddi [8] and Wang et al. [113], who also used structural models in testing the relationship among the variables of TAM and reported PU's larger effect on adoption intentions and attitudes toward use when compared to PEU. However, while some studies of this nature stop at intentions, see Abaddi [8], our research extended to actual usage, demonstrating that generative AI is not only intended but actively used for sustainability purposes. This means that other scholars such as Hicks et al. [42], who theorized that large language models are useless and have labeled them as "bullshit", cannot generalize their findings to other populations, nor should their conclusions dictate decisions on the viability of generative AI in sustainable applications.

Rather, our qualitative findings complement these quantitative insights, elucidating deeper how generative AI was useful for SMEs' sustainability goals. There were four primary uses: operational efficiency, sustainability-focused decision-making, sustainable product innovation, and building a sustainable brand identity.

Business owners leveraged generative AI to automate routine tasks like emails, order prioritization, and report generation for operational efficiency. Enhanced labor productivity in this study corroborates earlier findings that generative AI simplifies repetitive tasks and processes, freeing up time and resources for more meaningful pursuits [39,115]. This was how the SMEs in our study catapulted their social sustainability as they reallocated staff to focus on sustainability projects and community engagement initiatives, which were previously sidelined. Additionally, generative AI has significantly improved cost efficiency, allowing the SMEs to produce content that would otherwise necessitate costly expert input or attendance at expensive sustainability conferences. These cost savings align with the triple bottom line theory principles, which emphasize that economic sustainability need not be compromised in pursuit of environmental or social goals [19]. In this context, generative AI is a powerful catalyst, encouraging SMEs to continue their commitment to sustainability initiatives [40].

Generative AI also played a critical role in sustainability-focused decision-making. This outcome contrasts with the findings of Hicks et al. [42], who suggested that generative AI is often misperceived and relies on hallucinated sources, urging caution in its application for decision-making. However, our study indicates this concern does not hold in our context. Instead, it empowered the business owners to make informed, sustainability-focused scenario comparisons across multiple areas. For example, some used it to identify "green" suppliers by analyzing a vast range of potential partners more effectively than by doing manual searches, offering them tailored options to make environmentally responsible sourcing decisions. It was used to complement other smart technologies to monitor energy consumption, leading to adjustments in usage and reduced wasted energy. These results are consistent with other research that found enhanced decision-making through AI has become increasingly important for resource efficiency in manufacturing industries [64,116]. Moreover, AI-driven scenario analysis helped SMEs weigh the pros and cons of various sustainability strategies, leading to more informed and strategic decisions reflecting the findings of Sipola et al. [40], Cresswell et al. [29], and Potla [28].

Additionally, when selecting environmentally aligned equipment, generative AI was used to compare brands based on sustainability markers, which aided in selecting eco-friendly options. In staffing decisions, generative AI was used to mitigate human bias, analyzing applicants for pro-environmental and altruistic traits, thus aligning hiring practices with their sustainability vision. AI also facilitated market analysis by summarizing customer feedback on sustainable products [26–28]. As explained by Akerkar [117] and P. Kumar et al. [118], AI-assisted demand forecasting provides insights into future sales trends, which in our study helped SMEs make informed investment decisions on sustainable products. Our results matched those in earlier studies in that AI-driven insights reduced reliance on potentially error-prone human predictions, enabling participants to make data-backed choices that balance environmental impact with business viability [39,113,119].

In the context of sustainable product and service innovation, generative AI significantly enhances idea generation and prototyping. SMEs leveraged AI to brainstorm eco-friendly products, refine processes, and design offerings aligned with triple-bottom-line criteria: profitability, environmental responsibility, and social impact. By providing access to global trend data and research on sustainable methods, generative AI empowered SMEs to innovate effectively despite resource constraints. These findings are reassuring, especially when previous research highlighted significant innovation barriers SMEs face in Trinidad and Tobago [13]. Given the Caribbean's slow progress on sustainability [120], our results align with earlier studies [121,122], confirming that generative AI holds substantial potential for fostering innovation. This technology appears useful to SMEs in meeting their long-term sustainability commitments.

Another noteworthy finding is that generative AI was crucial in building a sustainable brand identity. SMEs utilized it to craft tailored, engaging content that effectively conveyed their green values across platforms. By simplifying content creation, generative AI enables businesses to deliver sustainability-focused messages, strengthening their public image consistently. These findings align with those of Park and Ahn [123], who highlighted the importance of generative AI in shaping marketing strategies and influencing customer perceptions of brand identity. Moreover, by integrating AI into marketing and data analytics, businesses can enhance their market positioning and drive revenue growth, contributing to economic sustainability [67].

5.2. Ease of use of generative AI

The structural model analysis offered empirical evidence supporting the hypothesized relationships, where perceived ease of use (PEU) was found to significantly predict intentions to use and thereby active use. This finding reinforces that SME owners who perceive generative AI as easy to use are more likely to find it useful for achieving business objectives, including sustainability [1,113]. What stands out is the positive adoption of generative AI tools among SMEs, driven by their ease of use—an unexpected finding given the reported lack of advanced education or technical expertise among SMEs in Bahaw's [13] study on innovation barriers. This highlights the critical role of technologies designed with user-friendly interfaces and functionality tailored to non-experts. While our quantitative findings confirmed a positive association between the ease of use and intentions to continue using generative AI, our qualitative findings added depth, revealing that while SMEs faced skepticism about security, originality, and misinformation, these concerns did not impede adoption. Perhaps the most striking finding was what was not reported as a challenge. None of the participants mentioned that generative AI was difficult to use or lacked the technical expertise to use it, contrary to the challenges to AI adoption [67]. Also, no one mentioned any pay walls affecting its accessibility. In other studies, the ease of use of technology is usually hindered because of technological literacy barriers [47,67]. However, neither was the case in this study. Despite the challenges faced which were much like those in previous studies, see Rahaman et al. [39] and Sipola et al. [40], its ease of use appears to overpower these limitations.

5.3. Study contribution and implications

This integration of quantitative and qualitative findings highlights the transformative potential of generative AI for SMEs, particularly in small island developing states, where they operate in sectors susceptible to infrastructural or climatic risks. Tools that combine ease of use with tangible benefits are essential for fostering innovation and resilience. By addressing both operational and strategic sustainability needs, generative AI levels the playing field, enabling smaller businesses to implement practices once exclusive to larger firms. Despite challenges, the ease of use and utility present a promising pathway for SMEs to achieve sustainability goals.

5.4. Theoretical implications

Our research intersects three critical domains: technology, sustainability, and entrepreneurship. It contributes to the literature by integrating the TAM and TBL frameworks to examine generative AI's role in sustainable outcomes. This integration enriches the theoretical discourse on technology adoption and addresses significant gaps in understanding how AI facilitates sustainability, particularly within SMEs in small island developing states.

First, while TAM traditionally highlights ease of use and perceived usefulness as key drivers of adoption, we expand its scope by demonstrating how AI adoption supports economic, social, and environmental sustainability through the TBL lens. Through a quantitative approach, we confirmed that usability and ease of use influenced both intention to use and actual usage of generative AI. To deepen this understanding, we conducted qualitative interviews to explore how actual usage translates into sustainability-driven business practices. This represents a theoretical shift where the conventional metrics of technology acceptance are supplemented with sustainability criteria. This shift encourages scholars to consider broader implications of technology adoption, particularly regarding long-term sustainable development goals.

Second, in our work, we elucidate four dimensions, namely (i) operational efficiency, (ii) sustainability-focused decision-making, (iii) sustainable product innovation, and (iv) sustainable brand identity. These dimensions suggest that the perceived usefulness construct can be reconceptualized to include sustainability benefits, expanding the theoretical understanding of technology acceptance in entrepreneurial settings. By integrating sustainability criteria into the adoption narrative, we refine the applicability of TAM, demonstrating that perceived usefulness is not only about efficiency and performance but also about technology's capacity to drive economic viability, social responsibility, and environmental stewardship, which are core tenets of the triple bottom line (TBL) framework.

Moreover, the underexplored context of SMEs in small island developing states provides a context-rich case to view the adaptability and impact of emerging technologies in varying economic conditions. Our findings suggest that these factors influence the applicability of established models, emphasizing the need for context-sensitive theoretical frameworks that account for variations in adoption behavior across different economic environments.

Finally, our research highlights the importance of interdisciplinary studies, encouraging future inquiries that fuse technological innovation with sustainable entrepreneurship. Scholars are prompted to explore mixed-method approaches that capture adoption mechanisms and their broader sustainability impact.

In closing, our theoretical implications not only deepen the dialogue around technology acceptance and sustainability but also advocate for expanding existing models to account for the multidimensional nature of technology adoption in various contexts, thereby expanding understanding of how generative AI can propel sustainable outcomes in diverse settings.

5.5. Practical implications

Our findings offer actionable insights for SME founders and generative AI developers. For SME founders, particularly in small island developing states, we encourage adopting generative AI. Its use can enhance profitability, sustainability, branding, reduce waste, enhance strategic management, and automate routine tasks, thereby boosting employee well-being. SMEs can contribute to environmental and social sustainability simply by using generative AI. Given its ease of use, SME owners can consider training all levels of staff on how they can incorporate it to support their daily duties. In addition, for AI developers, our study highlights the importance of retaining the user-friendly components of their generative AI product offerings. They can consider designing a tailored form of generative AI that is trained to assist SMEs in improving their sustainability. For instance, AI developers should consider embedding sustainability-specific features, such as carbon footprint tracking, automated compliance with environmental regulations, and AI-driven sustainability reporting tools. These innovations can enhance SMEs' ability to meet sustainability targets while optimizing operational efficiency.

Furthermore, developers should ensure that features like content, text, and image generation remain accessible and practical for business needs. Moreover, privacy and accuracy concerns should be addressed for greater adoption. Finally, we encourage collaboration between SMEs and technology providers that can help bridge knowledge gaps and drive more effective AI implementation tailored to sustainability goals.

5.6. Policy implications

Policymakers are encouraged to support this transition through targeted educational programs that raise awareness of generative AI's potential for economic, environmental, and social sustainability. Public workshops and entrepreneurship development agencies can play pivotal roles in demystifying these tools and promoting their accessibility. Such initiatives can empower SMEs to confidently adopt generative AI, driving sustainability and benefiting society and the environment. Additionally, policymakers and business support organizations should facilitate SME access to generative AI by offering digital infrastructure support. SMEs in small island developing states often face significant barriers related to technological access. Given that generative AI heavily relies on internet connectivity, we urge the governments of these regions to prioritize improving internet availability. They can encourage internet service providers by offering incentives to ensure nationwide coverage, as there are areas where connectivity remains limited.

Finally, we do not see the need for governments to allocate financial incentives such as tax breaks to encourage AI adoption, as our study shows strong acceptance and readiness to use generative AI among SMEs, despite the few challenges experienced. Instead, these financial resources would be better spent investing in the technological infrastructure mentioned above to enhance accessibility hurdles that often constrain SMEs operating in SIDs [124].

6. Conclusion

This study aimed to explore the role of generative AI in enhancing business sustainability, particularly among SMEs in the context of a small island developing state, namely Trinidad and Tobago. By integrating the Technology Acceptance Model and the Triple Bottom Line framework, the research revealed significant insights into the adoption and application of generative AI. Quantitative findings confirmed that perceived ease of use and usefulness positively influence intentions to use and actual usage of generative AI. As such, all hypotheses in this study were supported, suggesting that the TAM provides a valuable framework for understanding why SME owners in our sample utilized Generative AI. In doing so, we also addressed calls from previous studies highlighting the need to apply TAM in non-Western contexts and smaller firms [1,19]. Our findings demonstrate the replicability of the framework when applied to different technological applications, as seen in our case with Generative AI. Moreover, our qualitative data highlighted its contributions to operational efficiency, sustainable product innovation, data-driven decision-making, and building sustainable brand identities. Despite concerns such as security risks and misinformation, generative AI was shown to enable SMEs to overcome resource constraints and foster sustainability. In short, we conclude that, at least in this sample of SMEs, Generative AI is useful in achieving business sustainability. Overall, this study highlight the transformative potential of generative AI as an accessible gateway for SMEs in small island developing states to achieve sustainability goals while navigating the challenges of limited resources and competitive markets.

Finally, our study has limitations readers should consider when interpreting our findings. First, focusing on SMEs within a single small island developing state limits generalizability, and the reliance on self-reported data may introduce bias. Future research could address these gaps by expanding the scope to include multiple SIDS, enabling cross-country comparisons to understand regional differences in generative AI adoption better. Second, while we employed mixed methods to address gaps arising from reliance on cross-sectional quantitative or qualitative studies, causation cannot be inferred from our approach, highlighting the need for longitudinal studies. Future work could explore the long-term sustainability impacts of generative AI, assessing how continuous use influences environmental, economic, and social outcomes over time. Notwithstanding these limitations, our study is significant as it sheds light on the transformative potential of generative AI for sustainability in SMEs within SIDS. It provides a crucial foundation for understanding how technology can address sustainability challenges in resource-constrained environments, guiding future research and policy efforts.

Ethical statement

Our university's institutional review board approved both phases of this study, with reference numbers CREC-SQ.2700/05/2024 for the quantitative phase and CREC-SA.2744/06/2024 for the qualitative phase. Participant consent was secured before data collection began, and no identifiable information was recorded during the data collection process to protect anonymity and confidentiality.

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CRediT authorship contribution statement

Priscilla Bahaw: Writing – review & editing, Writing – original draft, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **David Forgenie:** Writing – review & editing, Writing – original draft, Visualization. **Ghulfam Sadiq:** Software, Methodology, Investigation, Formal analysis, Data curation. **Satesh Sookhai:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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