Renewable and Sustainable Energy Reviews 160 (2022) 112305

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

A holistic risk management framework for renewable energy investments

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ARTICLE INFO

Keywords:
Renewable energy investment risks
Renewable energy risk assessment methods
Multicriteria decision analysis
System dynamics
Agent-based modelling
Monte Carlo simulation
Developing countries
Sub-sahara africa countries
Holistic risk management framework
Analytical hierarchy process
Analytical network process

ABSTRACT

Private investments are critical enablers to achieving energy access for over 770 million people worldwide. Despite decreasing capital costs, investments in renewable energy (RE) projects in developing countries are low due to unattractive risk-return profiles. Through understanding key risks drivers and their interactions, actionable insights can be drawn to mitigate investment risks, making energy more accessible.

This paper reviews RE risks and methods used for risk assessment and mitigation for developed and developing countries with a focus on Sub-Saharan Africa countries (SSA). The review finds that while risk analysis and evaluation mainly employed semi-quantitative multicriteria decision analysis (MCDA) and system dynamics (SD) methods for developing countries, qualitative methods were used to identify mitigations. The methods assessed technical and economic risks at a minimum, while MCDA and SD methods can assess social, political, and policy risks. The efficacies of mitigations were tested using SD and quantitative methods such as agent-based modelling and Monte Carlo simulation.

The paper further introduces a 'holistic multi-dimensional investor risk management framework' which can be used to identify actions to improve investment risks in a structured manner. The framework addresses four fundamental limitations observed in the existing literature, recognising that RE risks are complex and involve multidisciplinary perspectives having interactions and feedbacks with other risks, actors, and their actions.

This review provides a valuable reference to investors, policymakers, and researchers, providing a catalogue of risks, methods deployed in literature, including a framework to identify impactful actions to improve risk levels.

1. Introduction

Affordable energy is vital to the socio-economic growth of any society. This is recognised by the United Nations Sustainable Development Goal (SDG) 7, which aims to ensure "universal access to affordable, reliable, sustainable and modern energy for all" by2030.[1] In achieving this goal, SDG7 seeks to increase the share of renewable energy (RE) in the global energy mix substantially by 2030. About 75% of people without reliable energy access worldwide live within lower-income Sub-Sahara Africa (SSA). More than half of the unelectrified African population live in rural areas, typically low-density remote areas far from electricity grids, making decentralised energy systems a viable solution to bridge the energy access gap [1,2]. Consequently, some scholars argue that a mix of grid extension, off-grid and standalone systems are needed to bridge the gap [2–4].

RE investments increased globally from US$ 200 billion to US$ 315 billion between 2005 and 2018 [5]. This increase is driven mainly by lower capital costs due to technological advances and volume induced savings in wind and solar PV technologies.[2] However, there is a need to increase RE investments to an estimated US$ 600 billion worldwide by 2030 to widen energy access while meeting climate change targets [5]. The investment deficit is higher for SSA, where studies have estimated US$ 11-9 billion/annum compared to annual investment needs of US$ 40–43 billion [6,7]. In SSA, power sector investments are primarily funded by the public sector with reliance on international development finance and grants [8–12]. Studies identified a scale-up in private investments as a critical enabler to bridging this gap [6,13,14]. Low investment in RE projects in developing countries is attributed to capital intensiveness and unattractive risk-return profiles [9,12,13,15,16]. Additionally, Zeng et al. [13] identified limited financing channels and poor adaptability of policies to changing markets and, consequently, risks and opportunities as contributors. Derisking policies and incentives are a means of unlocking RE potential [8,17,18]. Different investors weigh opportunities and risks differently between countries [19]. Understanding risks, risk levels, and their dynamic interactions from the

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[1] https://www.worldbank.org/en/topic/energy/brief/sustainable-development-goal-on-energy-sdg7-and-the-world-bank-group Accessed September 19, 2020.
[2] https://www.iea.org/data-and-statistics?country=WORLD&fuel=Renewables%20and%20waste&indicator=RenewGenBySource Accessed: October 18, 2020.

https://doi.org/10.1016/j.rser.2022.112305
Received 3 August 2021; Received in revised form 17 December 2021; Accepted 20 February 2022
Available online 4 March 2022
1364-0321/

List of abbreviations

ABM	Agent-based modelling
AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
CSP	Concentrated solar power
DEMATEL	Decision-making trial and evaluation laboratory
DRE	Decentralised Renewable Energy
EV	Electric vehicle
FiT	Feed-in-tariffs
ISO	International Standards Organization
IT2	Interval type 2
MAD	Market disclaimer approach
MCDA	Multicriteria decision analysis
MCS	Monte Carlo Simulation
NPV	Net present value
NS	Not Specified in the literature
PDF	Probability distribution function
PV	Photovoltaic
RA	Risk Analysis
RE	Renewable Energy
SA	Sensitivity Analysis
SD	Systems dynamics
SDG	Sustainable Development Goal
SSA	Sub-Sahara Africa countries
TE	Techno-economic
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

investor perspective can enable a more deliberate approach towards identifying appropriate actions that can lower investment risk exposure. This holistic understanding can provide more clarity on drivers of changes in key risks. Insights on the impact of mitigations, such as policy actions on improving financing conditions, cost competitiveness, and accelerating diffusion, can make RE investments more accessible and affordable [18,20,21].

There are three main strands of research employing RE investment risk management methods focusing on: risk identification [16,22–26], risk assessment [12,16,20,27–30] and risk mitigation [8,10,15,31,32]. Ioannou et al. [33] offer a review of risk analysis methods, while Painuly et al. [34] provide a framework for identifying RE penetration barriers and possible measures to overcome them. Within the existing body of literature, the review and application of risk methods are fragmented. This paper offers three contributions; firstly, it expands the scope of previous reviews [33,34] and presents a systemic review of RE investment risks and methods used for risk assessment and mitigation for developed and developing countries. Secondly, insights are drawn to introduce a 'holistic multi-dimensional investor risk management framework'. The framework unifies four key considerations treated in a fragmented manner in existing literature: consideration for (i) multi-dimensional perspective of risks (ii) interdependencies of risks and interactions within a complex system, (iii) dynamic nature of risks and (iv) holistic approach to risk identification, assessment, and mitigation of priority risks. Lastly, the new framework is reviewed from an SSA perspective and identify suitable methods that could be employed to determine specific actions to reduce investor risks and consequently improve energy access in a structured manner.

The objectives of this paper are to (i) critically assess methods used in literature for assessment and mitigation of RE investment risks for developed and developing countries, (ii) identify specific risk factors and appropriate risk management methods, and (iii) propose a conceptual framework that uses a holistic approach to identify actions for managing investment risks.

The paper is structured as follows: Section 2 provides an overview of risk management. Section 3 sets out the methodology. Findings on risk identification are presented in section 4, while findings on risk analysis, evaluation, and mitigation methods are presented in section 5. Section 6 presents a conceptual framework for holistic risk management, discussions, and considerations from an SSA perspective. Section 7 offers conclusions.

2. Overview of risk management

ISO 31000 [35] defines *risk* as the effect of uncertainty on an organisation's ability to meet its objectives. Additionally, *barriers* may also introduce challenges to achieving an organisation's objective. IRENA [24] defines barriers as obstacles or challenges in developing, financing, investing in, or operating projects. Project development risks and barriers can increase investors' perception of the overall difficulty of the investment environment. Hu et al. [36] note that actual and perceived risk factors influence the risk of RE investment. Risk perception is a function of risk judgement (defining risk levels) and risk attitude (reflecting the emotional attitude of an investor towards a judged risk) [36], which can impact an investment decision. Attributes that can increase risk perception could be in the form of psychological, behavioural or institutional characteristics such as lack of knowledge and experience or path dependence where historical investments in a particular technology, e.g. thermal generation, may impact RE risk perception and investment decisions [36]. These attributes need to be considered contextually due to the impact on perceived investment value proposition and corresponding investment decisions.

ISO 31000 provides the guideline for effective risk management which includes (i) establishing the context, (ii) risk identification, (iii) risk analysis, (iv) risk evaluation, and (v) risk treatment [35,37].

In establishing the context, the following needs to be considered: scope of the project, its boundaries, location, stakeholders, their objectives, and what level of risks are considered acceptable. The next step is to analyse the risks to determine risk levels based on likelihood and consequence. These risks are prioritised at the evaluation stage to determine acceptability. Outputs from this stage determine which risks require treatment. Risk treatment involves the implementation of controls to mitigate risks. This study uses 'risk mitigation' instead of 'risk treatment,' which is more prevalent in the reviewed literature. The risks are reviewed and updated at each risk assessment and mitigation stage via stakeholder communication and consultations.

3. Methodology - identification and selection of relevant studies

This section provides the methodology for identifying and selecting relevant studies, including analysis of papers along spatial and temporal distributions and an overview of reviewed methods.

Scopus searches limited to years 2010–2020 were conducted with keywords 'Investor risk renewable energy investment' (242 papers), 'Investor risk economic renewable' (111 papers). Abstracts were reviewed for relevance, and additional studies were identified by reviewing references of papers. This snowballing approach allows for the identification of topical papers more reliably than database search; however, results are dependent on the starting papers [38,39]. On scrutiny of articles, a total of 42 papers were selected based on coverage of risk management methods and classified where applicable according to technology application, location, and method. Papers related to assessing effectiveness of mitigations such as policy actions were classified under risk mitigation. Papers outside of these classifications were excluded from the review.

Figs. 1 and 2 show the distribution of papers. Geographically, 52% of

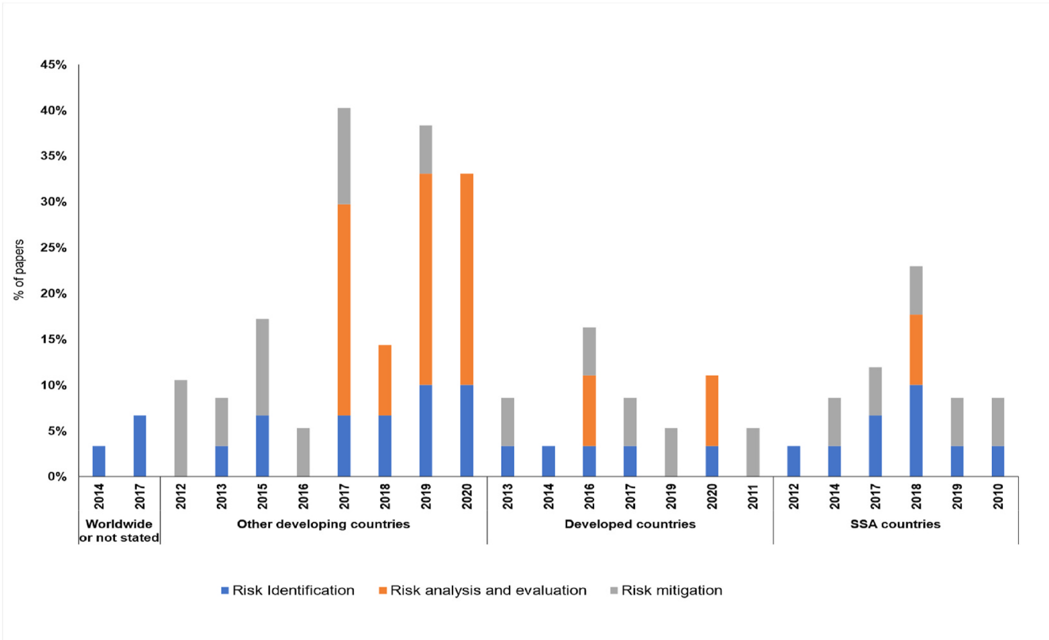

Fig. 1. Geographical and temporal distribution of reviewed papers.

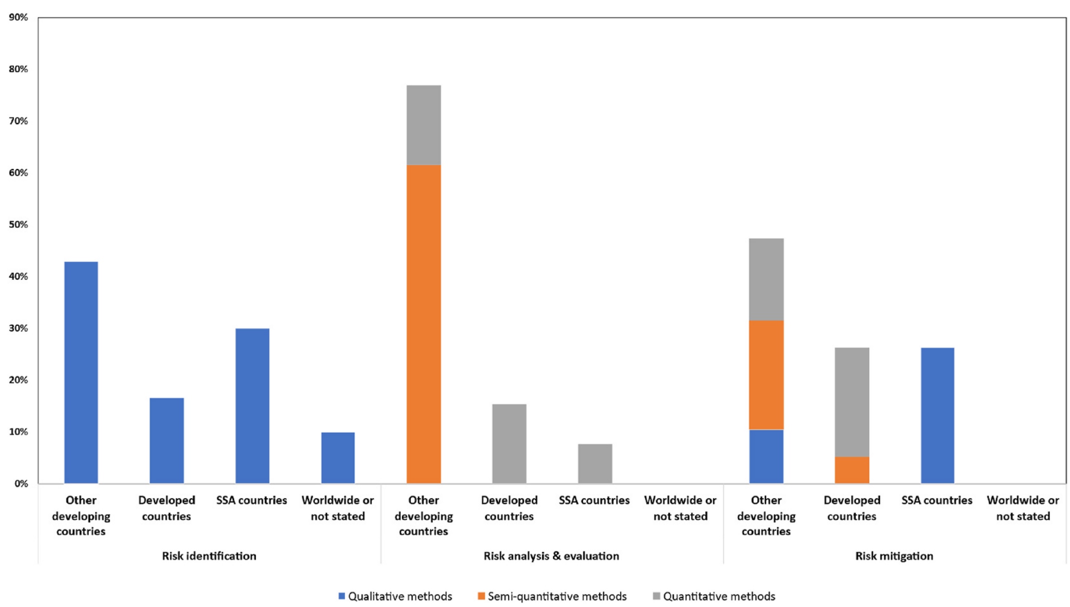

Fig. 2. The distribution of studies by methods and relevance to risk management framework.

studies covered other developing nations like China, while 24% and 19% of studies covered SSA and developed countries, respectively. More focus has been on semi-quantitative risk analysis and evaluation in other developing countries than SSA in the last five years. While studies covering developed countries focused on quantitatively determining the effectiveness of mitigations, papers related to SSA mainly focused on the qualitative identification of risks and mitigations.

Fig. 3 presents an overview of methods reviewed in the literature. Qualitative methods ranging from literature reviews to interviews and surveys have been used for risk identification, while risk analysis (RA) and evaluation have used semi-quantitative and quantitative methods. Risk mitigations were identified via qualitative methods, while quantitative methods tested their effectiveness.

Findings from the literature review are arranged in the following order according to the risk management framework and grouped based on methods, spatial distribution, application, and coverage of risk factors. RA, evaluation, and mitigation are grouped in the same section for continuity as similar methods have been used in literature.

(i) Risk identification.
(ii) RA, evaluation, and mitigation.

4. Review of RE risks identification

4.1. Risk classification and coverage

Classification of RE risks was done broadly according to barriers or uncertainties by focusing on (i) location, (ii) stakeholders (iii) project

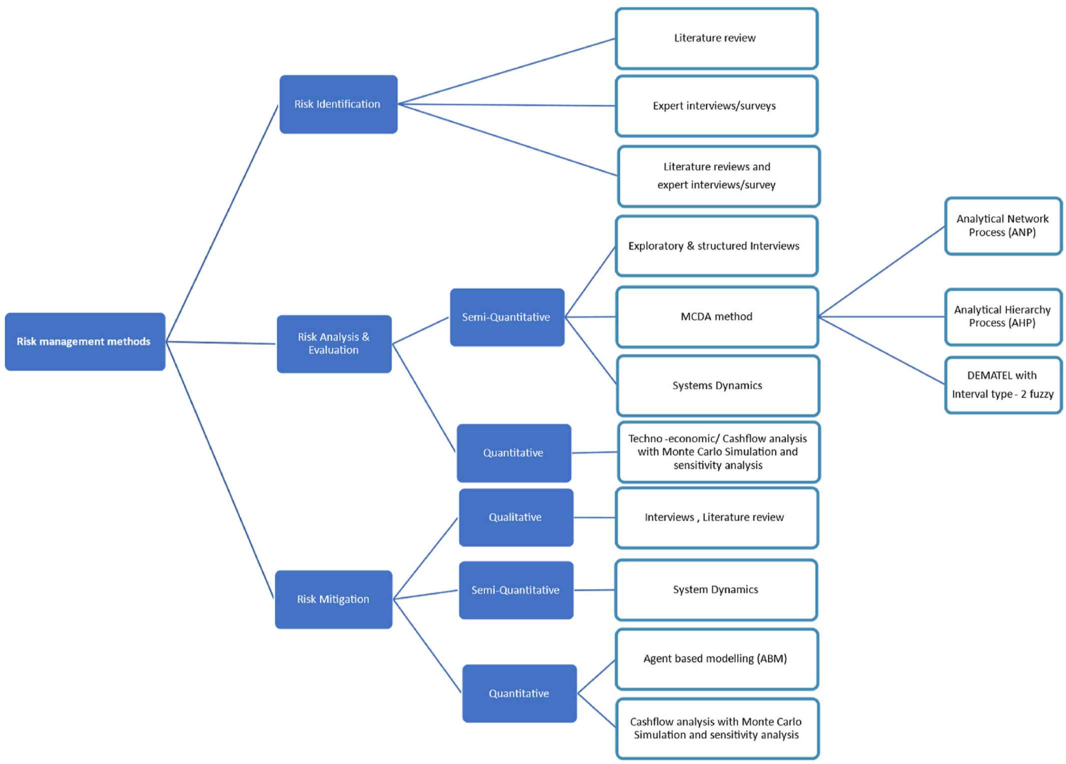

Fig. 3. Overview of RE risk management methods in the reviewed literature.

phases.

Within these broad rationales, barriers have been categorised differently according to the focus of the study. For example, Soshinskaya et al. [25] categorised barriers into technical, regulatory, financial and stakeholder barriers, whilst Williams et al. [40] identified technical, financial and policy/regulatory barriers as crucial barriers to RE uptake in developing countries. Bhattacharyya et al. [22] found technical, policy, financial, revenue, and political risks as factors impacting mini-grid implementation to scale in developing countries. Schmidt et al. [8] additionally considered risks according to barriers that stem from stakeholders at local, national, and international levels along revenue sources. This approach enabled a line of sight between barriers to revenue and measures required at the different stakeholder levels. Malhotra et al. [12] classified risks according to barriers from stakeholders who influence the cost of financing for a portfolio of projects. Risks were categorised such that they are mutually independent to enable independent analysis. Interactions were thus not considered. In contrast, Liu et al. [29] considered that risk factors dynamically change through feedback loops. This approach provided a system perspective involving risks and their interactions.

Different barriers can translate into investment risks at different project phases thereby, discouraging investments [8]. Hu et al. [36] grouped risk factors according to the stage of the project (preliminary risk scanning, appraisal, capital access, and project development stages) with a view that as projects mature, more information becomes available, and the level of uncertainty becomes clearer. Additionally, as a project matures, the type or level of risks can also change. Barroco et al. [41] classified risks according to project phases (feasibility, pre-construction, financing, construction, operations phases) and in the context of developing countries. The study provides a view of how risks change with project phasing. Knowledge of risks per project phase provides an opportunity to address risks timely.

Risk identification studies in the literature have used different risk categorisation themes according to their intended study focus. Some studies identified barriers without formal categorisation, e.g., inadequate technical skills, poor policy frameworks, and access to finance [23,42–44] as barriers to RE in SSA. This review uses the following definitions adopted from the literature to standardise the categorisation of risks.

- **Technical risks** arise from factors related to the type of technology, e.g. technology maturity, resource capacity and factors that can affect the technical design and implementation [29,40].
- **Resource risks** are the risk of lower revenues due to inaccurate resource potential estimation, such as variability or intermittency of radiation in solar development [20,29].
- **Policy and regulatory risks** refer to uncertainties in meeting project objectives due to legal frameworks, policies, or regulations changes.
- **Political risks** arise from political events that can impact investments, e.g., government change, political will, institutional structures, security events, embargoes, and currency inconvertibility [28,29,36,43].
- **Economic and financial risks** may arise from economic or financial factors that impact the project value or deployment. These can include changes in the economic environment on the macro level, e.g., currency fluctuation, uncertainties in accessing appropriate financing, revenue uncertainty [22,40–42].
- **Market risks** refer to uncertainties brought by variation in markets, e.g., market access barriers, changes in market conditions [22,29,36].
- **Curtailment risks** account for lower revenues due to unexpected curtailment [20].
- **Social risks** emerge due to changes in social conditions, e.g. public resistance impacting adoption patterns, demography [28].
- **Environmental risks** may result from changes in environmental regulations or impact caused by characteristics of energy systems, e.g., toxic waste, emissions [45].

Table 1 presents a comprehensive list of risks by these categories.

Table 1
Risks to RE deployment in various regions from the reviewed literature.

Risk Category	Risk Factors	Developed country	Developing country - other	Developing country - SSA	Reference
Technical	Technology maturity	•	•	•	[13,24,28,30,44,46–48]
	Technology progressiveness impacting on efficiency and quality	•	•		[25,28,29]
	Limited technical skills and capacity in operations and maintenance		•	•	[8,12,23,24,40,42,43,49,50]
	Limitation in developer's capability to effectively design, construct and operate a project		•		[8,12]
	Limited training, research, and development capacity		•	•	[28,29,42,49]
	Availability of alternative technology		•	•	[23,28,29]
	Limitations in the quality control and availability of hardware		•	•	[12,43,49]
	Variability in demand leading to uncertain load profile		•	•	[8,16,28,40]
	Uncertainty in population distribution patterns		•	•	[40]
	Higher maintenance cost due to technology novelty and unpredictability	•			[20]
	Limitations with dual-mode operations, i.e., grid to off-grid transitioning for grid-connected systems	•			[25]
Resource	Uncertainties in estimating power potential and its variability	•	•	•	[16,20,24,28,30,43,48,50]
Policy and Regulatory	A retroactive change in policy, e.g., feed-in-tariff, tax, regulation	•	•	•	[20,26,28,29,44]
	Inability to efficiently and transparently administer mini-grid related licensing and permit.		•		[12,41]
	Uncertainty in grid extension plans and technical regulations for integration of mini-grids into the main grid		•	•	[12,22,40,50,51]
	Lack of long-term policies			•	[42,49]
	Insufficient supporting policy frameworks and incentives, e.g., low support for foreign direct investments, high taxes, disparity between energy policies and development blueprint and uncertain fiscal policies		•	•	[23,29,36,42,43,48,49,51]
	Policy and regulatory uncertainty, e.g., policy consistency, implementation	•	•	•	[22,25,40,42,44,46,50]
	Difficulty in acquiring land, competition with land uses		•	•	[28,41,43,49]
	Unattractive regulated tariff		•	•	[8,36,40,43]
	Limitations in regulations on interconnection of mini-grids to main grids and enabling bi-directional flow of power mini-grids to main grids	•			[25]
Political	Effect of political changes, e.g., reshuffling of institutions.		•	•	[22,28,42,51]
	Complex Institutional structures with overlapping responsibilities		•	•	[8,40,43,51]
	Insecurity of infrastructure			•	[43,49]
	Political events that adversely impact the value of investments (e.g., war, currency inconvertibility, breach of contract, non-honouring of obligations)		•	•	[24,49,52]
	Bribery and Corruption		•	•	[28,42,50]
	Lack of political will to diversify into clean energy			•	[42,44,49]
	Legislative changes		•	•	[28,44]
	Political decision making and target setting impacted by political will, political cycle, influence of vested interest and perception on a social mandate to act	•		•	[47,49,50]
	Inadequate decisions and non-involvement of relevant experts in energy decision making			•	[49]
Economic/ finance	High initial cost		•	•	[22,43,48–53]
	Limited access to affordable finance		•	•	[8,22,24,29,30,40,42,50]
	High-interest rate		•	•	[23,30,40,41,44,50]
	Refinancing risk – Inability to secure loan refinancing due to mismatch between short loan terms and project lifetime.		•	•	[24]
	Currency risk - Foreign exchange challenges leading to cost-revenue mismatch		•	•	[12,16,24,28,41,52,53]
	Limited domestic investor capital		•		[8,12]
	Risk of price volatility within a stable policy regime	•	•		[20,30,53]
	Poor economic conditions		•		[28,41,49,50]
	Limited experience in the financial sector and domestic investors' lack of familiarity with RE		•	•	[22,24,48,49]
	Off-taker risk - Revenue uncertainty due to default by off-taker, potential customers with insufficient financial track records, unwillingness to pay, low affordability, seasonal income		•	•	[12,22,28,30,40,41]
Market	Sensitivity of competitiveness of RE to prices of conventional energy sources		•	•	[16,23,41,43,44,50,53]
	Market fluctuations due to speculative markets, e.g., land, foreign exchange markets		•		[28]
	Market distortion issues: Market access barrier, non-market-oriented research for solar energy technology and application, unavailability of investment-ready projects			•	[22,24,29,42]
	Limited market and consumer data availability		•	•	[8,22,51]
	Vulnerability to external market volatility due to dependence on imports		•		[29]

(*continued on next page*)

Table 1 (*continued*)

Risk Category	Risk Factors	Developed country	Developing country - other	Developing country - SSA	Reference
Curtailment	Lower revenues due to unplanned curtailment, e.g., grid bottlenecks	•	•		[12,20]
Social	Inability to gain buy-in and trust of constituents for development of mini-grid	•		•	[25,40]
	Construction of social relationship network in an unfamiliar investment environment		•	•	[28,40]
	Poor understanding of customer needs or usage patterns		•	•	[8,50]
	Public resistance to change to RE technology		•	•	[12,28,42,48,49]
	Poor awareness of solar benefits			•	[42,48–50]
	Instability caused by social events, e.g., riots		•		[28,52]
	Uncertainties in consumer technology adoption pattern and societal attitudes	•			[47]
Environmental	Public resistance to projects due to environmental influence		•		[28]
	Force majeure e.g. due to natural disasters		•		[28,52]

*Countries are grouped based on the United Nations classification [54].

4.2. Risk identification methods

Painuly et al. [34] broadly identified the following three complementing approaches to identifying barriers in RE: analysis of existing literature via literature survey, insights from site visits to existing projects and interactions with stakeholders through interviews and questionnaires. In application, scholars mainly use three qualitative risk identification approaches: analysis of previous studies via literature reviews, survey/questionnaires, interviews, or a combination. 70% of papers studied reviewed existing literature for barriers and risks related to similar locations or technologies. 27% of studies used a combination of literature review and surveys or interviews to identify risks. Malhotra et al. and Egli et al. [12,20] conducted a combination of literature review and exploratory interviews to identify the most relevant risk given the location, technology, and timeframe of the study. While Mohamed et al. [55] used a combination of literature reviews to establish risks and questionnaires/surveys to identify important risks. Schmidt et al. [8] iteratively used a combination of field research (including interviews) and literature review to identify barriers and mitigation measures for RE investments in Indonesia. Wells et al. [46] used interviews for risk identification.

Literature review provides a good starting point and can allow an expanded review of barriers that could be applicable, whilst interviews can help narrow down specifics and provide further insights on interdependencies. Most studies that used interviews for risk identification went on to further analyse or evaluate risks.

5. Methods for RA, evaluation, and mitigation

RA involves understanding the causes, probabilities of occurrence and impact of risks [37]. Risk evaluation uses the output of RA to compare risks, their priorities and whether they are tolerable. The most relevant risks can then be focused on for risk mitigation.

Options for risk mitigation as set out by ISO 31000 include risk avoidance by not progressing the activity, taking the risk, removing risk source, changing likelihood or consequence, and risk sharing [37]. The process involves iteration between risk mitigation and evaluation as control is evaluated to test for acceptable risk reduction. A risk could be deemed acceptable if the cost of mitigation outweighs the benefits or the level is considered low against what is tolerable.

Risk assessment can be qualitative, quantitative, or semi-quantitative or a combination [37]. Ioannou et al. [33] conducted a systematic literature review of risk assessment methods and grouped findings into quantitative and semi-quantitative methods. Findings on methods are grouped using categorisation by Purdy [37]. Table 3 summarise findings categorised based on location, technology type, method, and validation methods where specified.

5.1. Qualitative methods

Qualitative risk methods are subjective assessments typically used when numerical data are inadequate, unavailable, or limited resources [57]. It may involve assessing the probability and impact of risks and identifying mitigations using subjective techniques. Methods applied in reviewed literature include interviews and literature surveys. Qualitative analysis is simple and can explain mechanisms that drive investment risks.

5.1.1. Literature reviews and analysis

Studies have identified barriers and recommended mitigations by reviewing and analysing data from existing literature. Studies [43,44,49,50] identified barriers to RE applications in Africa. They recommended mitigations such as adequate and enforceable policies with strong political will in financial and subsidy incentives, compensation for land use and encouragement of community participation or ownership to mitigate security issues. In these studies, the feasibility and impact of the mitigations were not further analysed.

5.1.2. Exploratory and structured interviews with literature review

Schmidt and Diemuodeke et al. [8,49] identified barriers to RE utilisation and possible mitigations. Schmidt et al. [8] conducted a barrier analysis to identify barriers, understand risks and consider measures to assist investors for RE based village grids in Indonesia. They identified that barriers could be along local, national, or international levels at project phases. Through interviews with investors, mitigations such as improving access to finance, policy reforms and fossil fuel subsidies redistribution were identified.

5.2. Semi-quantitative methods

Semi-quantitative methods have the flexibility to consider statistical and non-statistical risks [33]. These methods are characterised by interviews and placing numerical values to risk levels and priorities. The following section discusses three broad semi-quantitative methods identified in the literature: exploratory and structured interviews, multicriteria decision analysis (MCDA) and system dynamics (SD).

5.2.1. Exploratory and structured interviews

Malhotra et al. [12] conducted structured interviews to refine risks identified in literature and obtain quantitative ratings of likelihood and impacts using Likert scale. The authors determined the contribution of each risk category to the cost of capital using an approach proposed by Waissbein et al. [58]. The limitation with this method is risks were considered independently. The authors determined the effect of spatial diversification strategies on levelized cost of energy as a means of addressing risks and found that risk profiles of mini-grid projects can be

Table 2
Risk identification methods and categories in the reviewed literature.

Risk identification method	Region (Technology)	Reference	Risk category										Risk and barrier categorisation rationale according to:			% of reviewed papers
			Technical	Resource	Policy/ Regulatory	Political	Economic	Market	Social	Environmental	Curtailment	No categorisation	Location	Stakeholders and location	Project development stages	
Literature reviews	China, India, Brazil, Mexico, Russia, Indonesia, Turkey (Wind)	[52]				•	•	•	•				•			70%
	USA, Netherland, Japan, Norway (RE)	[25]	•		•		•		•				•			
	Africa (RE)	[23]	•		•		•						•			
	Developing countries (RE Minigrid)	[22]			•	•	•	•	•				•			
	Philippines (NS)	[41]	•		•	•	•		•	•					•	
	Nigeria (RE, fossil)	[51]			•	•	•						•			
	RE generation projects	[36]	•		•		•	•							•	
	Nigeria (solar)	[43]			•	•	•					•				
	Nigeria (Grid solar)	[42]	•		•	•	•	•	•				•			
	Worldwide (RE)	[24]	•		•		•	•					•			
	Worldwide (RE)	[53]										•				
	Asia (Solar PV)	[30]	•		•		•			•		•		•		
	Brazil (Distributed system)	[27]					•						•			
	Developing countries (RE Mini-grid)	[40]	•		•	•	•	•	•				•			
	Rwanda (decentralised RE and hybrid)	[16]	•	•			•	•				•	•			
	China (Wind)	[29]	•		•		•	•					•			
	54 developing countries (Grid and decentralised Solar)	[28]	•	•		•	•		•				•			
	Germany, France (wind)	[26]			•								•			
	Corte d'Ivoire (RE)	[48]	•	•	•	•	•		•			•	•			
	Africa (RE)	[50]	•		•	•	•		•				•			
	South Africa (RE)	[44]	•	•	•	•	•	•	•			•	•			
Exploratory and semi-	UK (RE)	[46]			•	•	•						•			3%

(continued on next page)

Table 2 (*continued*)

Risk identification method	Region (Technology)	Reference	Risk category										Risk and barrier categorisation rationale according to:			% of reviewed papers
			Technical	Resource	Policy/ Regulatory	Political	Economic	Market	Social	Environmental	Curtailment	No categorisation	Location	Stakeholders and location	Project development stages	
structured Interviews																
Literature reviews and survey	China (EV charging infrastructure)	[56]	•			•	•						•			7%
	India (Grid & decentralised Solar)	[55]	•		•		•						•			
Literature review, Exploratory and semi-structured Interviews	India (Mini-grids)	[12]	•				•				•			•		20%
Literature review, Exploratory Interviews/ focus group	Middle East (Power plant)	[45]								•			•			
	UK, Germany, Italy (wind, solar)	[20]	•		•		•				•		•			
	Indonesia (RE)	[8]	•		•		•	•						•		
	UK (Energy transition)	[47]	•		•		•						•			
	Nigeria (RE)	[49]	•		•	•	•	•	•				•			

NS - not specified in the literature.

Table 3
Review of methods for RA, evaluation, and mitigation.

RA, evaluation, and mitigation methods		Region (System)	Reference	Application		Risk category									Validation
				RA & Evaluation	Risk Mitigation	Technical	Resource	Policy/ Regulatory	Political	Economic	Market	Social	Environmental	Curtailment	
Qualitative methods	Literature review	Nigeria (solar development)	[43]		•			•	•	•					
	Literature review	South Africa (RE)	[44]		•	•		•		•	•		•		
	Literature review	Africa (RE)	[50]		•	•		•	•	•	•				
	Literature review and questionnaire	USA, Netherland, Japan, Norway (RE – grid and decentralised)	[25]		•			•		•		•			
	Literature review and expert	Indonesia (RE)	[8]		•			•		•	•				Interviews
	Interview	Nigeria (RE)	[49]		•	•		•	•	•	•	•			
Semi-Quantitative methods	Literature review, Structured Interview	UK, Germany, Italy (wind & solar)	[20]	•				•		•				•	Literature data and interviews
	Structured and exploratory interviews with Linkert scale	India (mini-grids)	[12]	•				•	•	•	•			•	
	Expert Interview with Delphi and Fuzzy set theory establishing likelihood and impact	Germany, France (wind)	[26]	•				•							Expert interview data
	AHP, Interviews/survey and Literature reviews	India (Grid & decentralised Solar)	[55]	•				•		•					
	Fuzzy AHP and Interview	Asia (Solar PV)	[30]	•				•		•					Literature review, expert interviews
	ANP-Cloud and Interviews with Delphi	Middle East, Russia, India (Grid & decentralised Solar)	[28]	•		•	•		•	•		•			
	ANP-Cloud and Interviews with Delphi for RA and fuzzy comprehensive assessment method for evaluation	China (EV charging infrastructure)	[56]	•					•	•					Expert interview with SA
	Literature review combined with Interval type 2 (IT2) fuzzy DEMATEL	China, India, Brazil, Mexico, Russia, Indonesia, Turkey (Wind)	[52]	•		•	•		•	•	•	•			Robustness check with IT2 fuzzy TOPSIS
	SD, cost-benefit analysis and SA (Assess policies for promoting solar PV)	Taiwan (Solar PV), Taiwan (Solar PV and heating)	[10,66]		•			•							Reproduction of historical data
	SD and SA (Assess policies for promoting solar PV)	China (Solar PV)	[67]		•			•							
	SD with scenario analysis (To evaluate policy effect on PV competitiveness	Spain (PV grid)	[68]		•			•							
	SD	China (RE)	[29]	•				•			•		•		Expert Interview
		Middle East (Power plant)	[45]	•									•		Interviews, focus groups
	SD	Malaysia (Solar PV)	[65]		•			•							Boundary accuracy and structural verification per [74]
Quantitative methods	TE analysis with SA	Rwanda (decentralised RE and hybrid)	[16]	•		•	•			•	•			•	
	SA and MCS combined with cashflow analysis (MAD) and real options approach	Indonesia (wind)	[70]	•		•	•	•		•			•	•	
	TE analysis and MCS combined with SA	Brazil (Distributed sys - diesel, gas)	[27]	•						•					

(continued on next page)

Table 3 (*continued*)

RA, evaluation, and mitigation methods	Region (System)	Reference	Application		Risk category									Validation
			RA & Evaluation	Risk Mitigation	Technical	Resource	Policy/ Regulatory	Political	Economic	Market	Social	Environmental	Curtailment	
Interviews and literature review with cashflow analysis	Egypt, Morocco, Tunisia, Algeria (CSP)	[9]		•					•					
	India (Mini-grids)	[12]		•		•			•					
Cashflow analysis & SA with MCS	Germany, France (wind)	[26]		•			•							Expert estimates
Cashflow analysis (marketed asset disclaimer approach) combined with real options, SA and MCS	Indonesia (wind)	[70]	•	•	•	•	•		•			•	•	
ABM (To test policy effectiveness)	EU (RE)	[72,75]	•				•							Reproduction of historical data
ABM (With SD)	US (Solar PV)													
ABM (To evaluate policy effect on investments, emissions, economics)	Indonesia (Solar PV)	[73]	•				•							

made more attractive by aggregating projects in a spatially diverse portfolio.

Egli et al. [20] drew on a mixed-method approach using existing literature data and exploratory and structured interviews combined with the Borda count method to identify and refine findings on the most important risks (given the context of technology, timeframe, and location). Borda count was selected for its straightforward interpretation and wide use [20]. This approach enabled corroboration and improvement of validity of findings. Network text analysis of interview data was used to identify risk drivers and links between risk types. Technology, price, policy, curtailment, and resource risks were most important to RE investments, with levels changing over eight years. The authors subsequently put forth a techno-economic model that considers the revenue impact of relevant risks. There was no analysis done on actions that can reduce risk levels.

Gatzert et al. [26] developed a framework for studying policy risks for RE investments. The authors used interview and fuzzy Delphi probability prediction method to obtain the likelihood and impact of the considered policy risk scenario. Mozuni et al. [59] defined Delphi as a survey technique used to gain consensus knowledge from a group of experts over multiple rounds. The model was calibrated using expert interview data for two countries and Delphi technique.

5.2.2. MCDA

MCDA is a family of decision support analysis methods used in the energy sector to evaluate alternative energy sources, policy analysis, decision-making, and consideration of risk perceptions due to their ability to incorporate multiple actors' opinions [33,60]. MCDA methods rely on relationships such as priority and outranking. It takes judgements from stakeholders to evaluate weighted priorities of decision alternatives. With regards to its application to risk assessment, outputs are usually in the form of risk ranking. The methods have therefore been applied to RA and evaluation. MCDA methods encountered in literature include Analytical Network process (ANP) [28,56], Analytical hierarchy process (AHP) [30,55] and decision-making trial and evaluation laboratory (DEMATEL) [52].

In the ANP method, a pairwise comparison of risks is made [61]. ANP allows for feedback and interaction – such that elements in a network can communicate with each other [28,62]. ANP combined with interviews presents flexibility that enables simultaneous use of quantitative and qualitative criteria, including review consistency [62]. For instance, Wu et al. [28] used Delphi combined with expert interviews to express the probability and consequences of risks in linguistic terms for 54 countries. The authors used a combination of ANP method to determine relationships between risks and weighting of risks and a cloud model to express linguistic terms to numerical form and assess risk levels. They grouped countries according to risk levels and provided recommendations for investors according to risk level.

Wu et al. [28] used a combination of interviews, ANP for weighting calculations and grey fuzzy assessment to prioritise risks for electric vehicle (EV) charging infrastructure, thereby identifying critical risk factors to be managed. The result shows that operation incomes, costs, industrial standards, and technical risks factors were most important. Robustness checks carried out include sensitivity analysis testing impact of (i) subjectivity in human judgement and (ii) expert sample size on risk values. Risk mitigations were suggested but were not further evaluated for their effectiveness.

AHP can also translate qualitative inputs into numerical relations. Mohamed et al. [55] used AHP to identify major risks and weightings, while Kim et al. [30] used a combination of interviews and fuzzy AHP to determine financial risk factors as the most important. The study showed differences in the relative importance of risk factors for the different stakeholders, which is essential in determining specific risk strategies. Fuzzy AHP considers that there is uncertainty in the human decision-making process. Although AHP conducts a pairwise comparison, it assumes factors in the hierarchical structure are independent, making it unsuitable for representing complex systems [63].

Qui et al. [52] applied combined two MCDA methodologies – Interval type 2 (IT2) fuzzy DEMATEL to determine risk levels and IT2 fuzzy VIKOR for risk ranking. The authors further deployed IT2 fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution; a fuzzy MCDA method) as a robustness check for ranking. Wang et al. [64] used fuzzy DEMATEL for determining which criteria were critical from RE investment and policy perspective. None of the reviewed studies further quantified risk mitigations.

5.2.3. SD

SD combines qualitative and quantitative analysis, including synthesis reasoning [29], to identify problems, primary variables, and interactions. SD is characterised by feedback loops and time delays to model complex system behaviours. The method can be used for sensitivity analysis and scenario simulations [65].

Liu and Al Mashaqbeh et al. [29,45] evaluated RE investment risks using SD and noted that static models could not adequately model RE investment risk complexity resulting from interdependencies and interactions.

Al Mashaqbeh [45] developed an SD conceptual model to assess non-technical risks for power plants considering interdependencies and the dynamic nature of risks. Li et al. [29] studied RE investments risks in China and developed an assessment model consisting of technical, policy and market risks sub-models to simulate system behaviours as a feedback system over ten years. The study determined how risk importance changes over time, which is vital for investment timing. Although the study analyses technical, policy and market risks, including interactions, it could be further improved by expanding to analyse other applicable risk factors to understand their importance. Risk mitigations were not explored in the study.

Another set of literature has deployed SD for policy assessments in support of RE investments. Hsu et al. [10] used SD with cost-benefit analysis to assess policies for promoting solar PV applications such as feed-in tariffs (FiT) and capital subsidies to achieve solar PV installation and CO_2 emission reduction targets under various conditions. Results showed that goals might be attained by applying reasonable FiT or subsidies, including some compulsory regulations and punitive measures. Historical data on solar PV installations between 2001 and 2010 in Taiwan were used to validate the model.

Trappey et al. [66] used a cost-benefit evaluation methodology based on SD to assess the effectiveness of policies and the corresponding benefits for carbon reduction. Guo et al. [67] used SD with sensitivity analysis to evaluate China's policy environment and interaction with variables considering technical and economic factors. The model was used to explore impact of policies on PV power generation, investment and installed capacity over 20 years. A limitation of the model is that it did not consider interactions such as energy sources, social, political factors with PV system investments. Movilla et al. [68] used SD to analyse the dynamic behaviour of the Spanish PV market under different support policy scenarios to assist policymakers in designing energy policies. Results indicate that the sector would be profitable with continued policy support and a gradual subsidy reduction with PV developments. The model was validated by reproduction of historical data.

5.3. Quantitative methods

Quantitative risk-based evaluation methods deal with statistical data and probabilities to determine risk levels, consequence analysis and risk reduction via numerical or computer-based models. Quantitative methods identified in the literature include Monte Carlo simulation (MCS), Sensitivity analysis (SA) combined with techno-economic (TE)/cashflow analysis, and agent-based modelling (ABM).

5.3.1. TE/cashflow analysis with MCS or SA

SA and MCS were combined with TE in the reviewed literature. TE combines technical parameters and financial metrics to assess the economic potential of a project.

SA is a simplified method that enables identification of the most impactful variables. For example, Okoye et al. [69] conducted SA to test the effects of fluctuations in inflation rate, loan interest rate, electricity price, loan repayment time, and income tax rate on NPV.

MCS is a method that allows for uncertain input parameters and can be employed to produce probabilistic valuation models which incorporate risk [33]. MCS has been applied widely in literature and integrated into financial models to determine cashflows and investment criteria ranges. MCS has been used in combination with other techniques such as SD [16,27], real options and cashflow analysis using market disclaimer approach (MAD) [70] and ABM to improve robustness of the model.

For instance, Williams et al. [16] conducted a quantitative study considering a range of scenarios, including various technologies and tariffs, to quantify the effect of technical design and business model on investor risks. Deterministic SA was used to identify important uncertainties. Probabilistic SA determined variables that contributed most to project risks as fuel price, foreign exchange rate, demand for electricity, and price elasticity which vary depending on technology and tariff structure.

Zaroni et al. [27] assessed the economic risk associated with decentralised energy systems in Brazil using MCS. Although not an RE system, the method is considered applicable, therefore included in this review. Similar to Williams et al. [16], a deterministic SA was performed to rank input variables by associating the variables with probability distribution functions (PDF). Using MCS, mean peak energy price, generators parameter, and fuel price were determined as the most impacting variables on NPV PDF.

Kim et al. [70] proposed a framework for investment decisions in RE projects for developing countries at planning, design, and construction phases. Steps employed in the study included cashflow analysis, real options valuation of RE project using 3-point estimate and MAD approach. SA and MCS were conducted to identify influential variables (tariff, energy production) and quantify their impact to arrive at decisions at the different project phases. Real options allow for incorporation of investor choices in decision making in the model. The authors emphasise risks associated with revenues and did not consider uncertainties in capital costs, such as access to affordable capital or policy changes during project phases.

Gatzert et al. [26] determined the impact of mitigations, e.g., changes in FiT and cross-country diversification, on risk-return profile using cashflow analysis with MCS and SA. Cross-country portfolio diversification and increased FiT over a short period were found to decrease the impact of policy risk on the risk-return profile. In determining this impact, the study assumed the independence of policy risk factors.

Bhattacharyya et al. [15] used discounted cashflow analysis to assess the viability of new policies to attract private investments in rural India when applied to small scale mini-grid and large-scale grid connect solar PV systems. The authors found mini-grid support such as subsidies or low-interest debt would be required to attract private investments under the studied policy regime, while large-scale solar projects were an attractive proposition for investors. The impact of risks on cashflow was not included in the analysis.

All the reviewed studies did not consider the interactions or interdependencies between risk factors.

5.3.2. ABM

ABM is a dynamic model consisting of agents with an ability for learning. It allows representation of behaviours and feedbacks of agents such as investors, consumers, policymakers by representing discrete decision-makers and focusing on agent decisions and interactions over time [71].

ABM was not used to assess risks in the reviewed literature but was used to evaluate policy effectiveness. These policies could be viewed as mitigations or responses to barriers. ABM has been widely used in market diffusion, technology adoption, policy evaluation for climate targets and investments. Schiera et al. [31] used ABM to assess the impact of regulatory schemes on adoption of rooftop PV. Zhang et al. [31] integrated ABM, real options and social networks to assess RE adoption. The model incorporates the customer risk preferences into real option decisions to determine the customer's willingness to invest. Chappin et al. [72] developed a modular ABM approach to explore electricity and emissions policies that can interact with each other and tested its robustness under uncertainties of input parameters such as fuel price and demand. Al Irsayd et al. [73] used ABM to evaluate policy effect on solar PV investments, emissions, and economic output.

6. Discussion

This section introduces a conceptual holistic framework for investment risk management to identify factors that can improve investor risk profiles. It further highlights key findings from the literature review, comparing methods used for risk assessment and mitigation. Findings are further discussed from an SSA perspective, drawing on existing literature to identify suitable methods.

6.1. Holistic multi-dimensional investor risk management framework

'RE investment risk evaluation is a complex system' [29]. Complex systems can be defined as many interacting parts known as actors, agents, or components [76]. Interactions between agents and their actions can result in effects that cannot be easily predicted by studying the individual agents. The impact of actions such as policy changes within these interactions can be better understood by identifying actions taken by the combination of actors [77]. This perspective can enable identification of impactful policies to mitigate risks.

The framework presented in Fig. 4 addresses four limitations observed in the literature, which may have been addressed in a fragmented manner within the existing body of literature.

Firstly, in assessing investment risks, many studies have focused only on techno-economic factors [27,40,70] or one key risk factor, e.g. Ref. [26]. Policy analysis has traditionally focused on techno-economic uncertainties. However, an inclusive, multidisciplinary approach that considers other perspectives enables more suitable solutions to address risks [47].

Risks need to be considered contextually. Policymakers and investors need to consider impact of location-specific risks, e.g., TE models may not incorporate location specific social risk factors in the analysis of investment parameters. Overlooking the impact of socio-economic risk factors such as affordability can lead to revenue risks. During decision making, investors need to consider the impact of human behaviours, such as a person's willingness to pay for and adopt a technology, on investments [78].

Secondly, many studies have addressed risks independently without considering interdependencies and interactions within the complex system. RE deployment involves actions and complex interactions between actors such as investors, developers, financing institutions, policymakers, regulators, and customers of various demographics. These interactions can be driven by factors such as environment, decisions, and actions taken by actors [77], which can be driven by risks resulting from multi-dimensional factors, e.g. social, market, economic, technical, political factors. For example, without considering interdependencies and feedback, it may not be apparent that a fossil fuel subsidy policy can introduce additional market risks for RE investments and may subsequently impact investments over time.

Thirdly, many studies do not consider the dynamic nature of risks. Risks can change over time, e.g., technological advances, the impact of policy change [20,68] and across project phases [36,41]. Understanding the dominant risk factors at a given project phase and period can provide focus on relevant risk and timely mitigations.

Lastly, whereas different aspects of risk management have been studied separately, the framework calls for a holistic approach to identifying, assessing, and mitigating priority risks using the ISO 31000 risk management guideline. By systematically following risk management guidelines and applying the multi-dimensions of risks and their interactions, an assessment of associated risk factors and their relative importance in terms of impact on investment decisions can be made. This can provide a more impactful approach to mitigating risks. The framework can be applied from different stakeholder and location perspectives.

6.2. Key findings on risk identification and methods

Out of the reviewed literature, 30% of papers identified risks and barriers applicable to SSA countries while 43% and 8% applied to other developing and developed countries, respectively. It is noted that although some investment risks categories can be generalised between developing (including SSA) and developed countries, risk causal factors

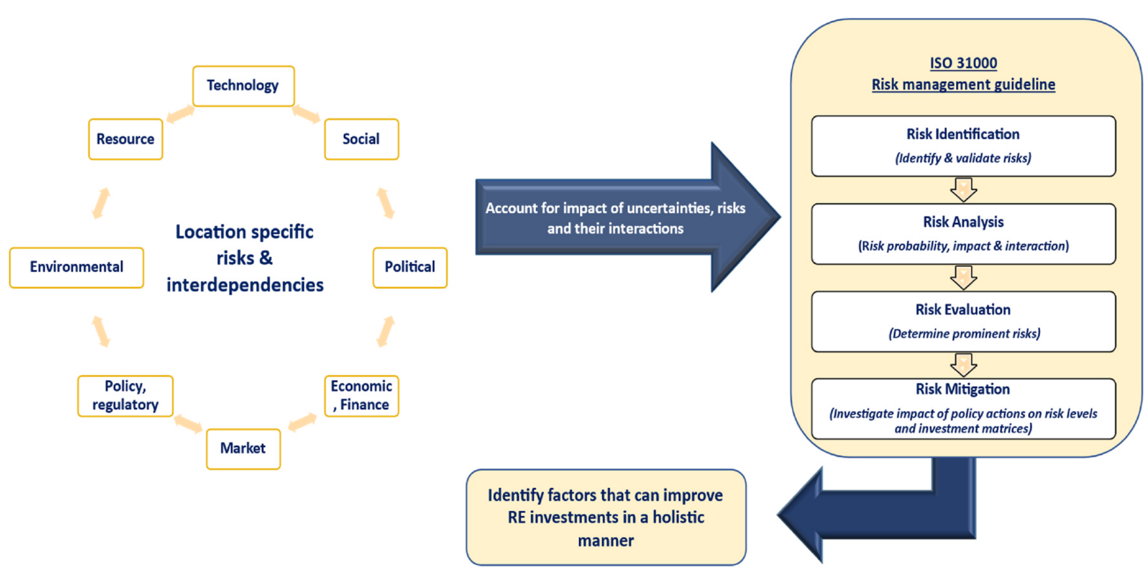

Fig. 4. Proposed conceptual 'holistic multi-dimensional investor risk management framework'.
Source: Adapted from Refs. [9,11,35,47].

and their level of impact may not be the same. For instance, developed country technical risks can be attributed to technological issues related to efficiencies, commercial availability of technologies and limited research and development [25,47]. In contrast, technical risks in developing countries include hardware quality and availability issues due to importation, limited availability of skilled personnel from project development through execution, competing alternative technology and technology novelty [8,12,40,43]. Policy risk levels also differ. Whilst developed country investments are open to risks due to retroactive changes in policy and tariffs, developing countries include policy inconsistencies and implementation uncertainties, insufficient policy frameworks for supporting investment and uncertainties in grid extension plans [20,28,47,51]. The dimensions of social and economic risk factors also vary significantly [20,26,40,47,50,79]. Developed countries social risk factors comprise uncertainties in technology adoption, changes in societal attitudes and demography. Social risks for developing countries can result from resistance to change due to lack of awareness of RE benefits, and revenue and demand uncertainty due to socio-economic conditions such as willingness to pay and low affordability. Although high implementation costs affect all countries, developing countries face further economic barriers, including lack of access to affordable capital, high cost of capital, the competitiveness of RE compared to alternatives, payment default, and limited domestic investors experience with RE [20,22,28,40,42].

In the review of risk identification methods (Table 2), literature review was the most prominent method, followed by interviews with literature review. Although easy to implement, literature review may not adequately identify relevant location-specific risks. Additionally, it neither captures the dynamic nature of risks that may vary across project phases and stakeholders nor provides an understanding of risk interdependencies with other risks and actors. It can be refined by supplementing with surveys or expert interviews. Results depend on the diversity and experience of the experts as well as the depth of interviews. Methods such as Delphi have been used in literature to achieve a consensus between experts [62]. Risk levels determined via expert interviews could be influenced by the number of experts and their subjective judgement. Therefore, it may be necessary to perform a SA to test the robustness of the responses [56].

6.3. Key findings on RA, evaluation, and mitigation

Of the reviewed literature, MCDA methods and TE or cashflow analysis with MCS and SA were most widely used for RE RA and evaluation. SD and ABM were mainly used to determine the effectiveness of risk mitigation approaches.

The impact of uncertainties on investment matrices has been tested by applying SA to TE [69]. Although easy to communicate, sensitivity changes are typically random without regard for the relative importance of the variables; this does not provide a reasonable basis for decision making [80].

TE has also been combined with interviews, SA, MCS and real options analysis in the case of Kim et al. [70] for RA and evaluation. In these studies, SA was used to quantify the impact of variables and MCS to identify the most important variable. Incorporating MCS to uncertainties in input parameters also produced probabilistic outcomes for cashflows. The results' accuracy depends on the statistical modelling of input variables and probability distribution function [33]. Input variables need to be statistically independent to prevent misinterpretation of results. Therefore, these methods did not account for feedback relationships between variables.

Furthermore, the sensitivities were only related to economic and technical risk factors. Williams et al. [16] noted the gap in quantifying risks for rural microgrids in SSA. They developed a TE model to quantitatively assess the impact of risk drivers on the business model and technology decisions using SA and MCS. However, the authors did not evaluate the effectiveness of the proposed risk mitigations. Further, although a detailed assessment of risk drivers was carried out, interactions between various risk drivers were not assessed. For example, it was considered that exchange rate impacts fuel price fluctuation; however, it was not considered that this could impact consumer disposable income, thereby changing demand patterns and thus affecting investor revenue.

A range of methods in the MCDA family was used in literature for RA and determination of risk priority levels based on interview or survey data. Methods used include AHP, fuzzy AHP, ANP-Cloud and IT2 Fuzzy DEMATEL methods. The impact of the proposed risk mitigations was not explored in the reviewed literature. Although MCDA allows for the use of quantitative and qualitative data, a general weakness is the inability to accommodate feedback between risks or criteria. Within the MCDA family, ANP allows for limited feedback and interaction. However, ANP cannot capture uncertainties in relationships due to exact or crisp values allocated to pairwise comparison [61]. In literature for decision making studies, fuzzy ANP was considered an improvement to ANP whereby instead of a crisp value, a range of values was applied to account for uncertainties in human judgements. However, fuzzy ANP poses the limitation of some alternatives incorrectly being ranked the same and consequently being treated equally. Noting this limitation, Hefny et al. [63] applied Gaussian fuzzy ANP to improve decision making among the alternative power generation scenarios. This method provided a more precise distinction between ranking alternatives than fuzzy ANP.

Gatzert et al. [26] conducted RA and evaluation using Fuzzy set theory combined with MCS, SA and cashflow analysis to estimate the impact of mitigation measures on policy risk reduction. Interactions of mitigations on other risks were not evaluated.

Complex interactions were modelled using SD and ABM. SD has been applied in RA [29,45] and to determine policy mitigation effectiveness [10,68]. These SD studies covered environmental, policy, and market risks. Al Mashaqbeh et al. [45] indicated that SD could also be applied to other risk areas. SD allows for modelling of complex systems from a cause-effect perspective which enriches analysis capabilities of the model [65]. SD requires comparably less quantitative data for building a model than ABM [72]. SD has its limitation in representing social interactions within social networks that can generate diversity of behaviours in individuals, such as willingness to adopt new patterns [70]. In comparison, ABM can be applied when choices and behaviours need to be incorporated into investment preferences. Although SD requires long-term data for model development and validation, the validation process is more structured than ABM and gives emphasis to qualitative information [71].

Movilla et al. [68] developed an SD model to simulate different futures against various policy scenarios. The model's validity was tested by reproducing historical data prior to running scenarios. Scenario review shows how policy changes may affect investments. The authors appear to assume that the investment decision parameters are solely payback period and profitability. Other investment decisions drivers that could be considered include portfolio comparison rather than individual projects, checks against investment criteria, NPV, debt service coverage ratios, political, and environmental drivers. Modelling investors as part of the SD model could improve the authenticity of the analysis.

Liu et al. [29] quantified the most important risks over time based on interactions with the system and other risks. The model was able to show that dominant risks change over time based on feedback loops. The authors note that risks considered were not exhaustive, which could impact system feedback loops. For example, one of the scenarios simulated reviewed the effect of increasing tariff subsidies; the resulting system behaviour was that policy risks decreased over time. As the government or regulatory body was not modelled as a separate actor, the developed system would not capture responses from the regulator. Such response could be to continue increase in tariff subsidies as modelled (this is unlikely due to limitation in budget), or where risk of policy change declines, the regulator could decrease or maintain a maximum tariff increase. This interaction or learning behaviour could be modelled using ABM due to its capability to model non-optimal decision-making and simulate learning behaviour of agents [81,82].

6.4. Review of risks from SSA perspective

RE investment risk is multi-dimensional, dynamic, location and stakeholder dependent. In addition to the risk factors discussed in section 6.2, further specific factors are highlighted for SSA. These include lower levels of in-country technical skills in manufacturing and implementation, insufficient supporting policy frameworks such as low support for foreign direct investments, high-interest rates and taxes, and policy uncertainties [23,44,48,50]. Studies highlighted socio-cultural and behavioural barriers such as poor awareness and negative perception of RE, security issues, non-involvement of relevant experts in decision-making, political, market, access to finance, and economic barriers [44,49,50]. Some studies looked into barriers to solar development, given its abundance in Africa [42,43] and cited political will, policy, incentives, availability of market data and security challenges as some of the barriers to implementation [42,43].

Within the same country, risk dimensions also vary across geographical areas and jurisdictions at national, state and local levels, as observed by Schmidt and Malhotra [8,12]. For instance, the importance of variability in demand due to population distribution patterns will vary between urban and rural areas characterised by low density, dispersed populations, and low incomes levels. Sparse populations require increased distribution infrastructure leading to elevated cost of development [83]. These differences will affect risk perception and risk levels and thus affect investment decisions. Therefore, to better understand effects and design appropriate measures to reduce risks and improve investments, it is necessary to focus on specific locations at local levels as implemented by Malhotra [12]. For example, aggregation of a spatially diverse portfolio can be a means to improve the risk profile whilst improving energy access. 90% of studies related to risk identification for SSA were carried out via literature survey. The studies can be improved via expert interviews using the Delphi method to provide a consensus of findings.

In determining suitable methods to assess these risks with a view of providing effective mitigations in form of policy actions, the following could be considered:

(i) Conformance to ISO 31000: Method(s) should have a holistic approach to assessing key investment risks and identifying mitigations.
(ii) SSA risk factors are multi-dimensional, and methods should be capable of assessing risks across technical, social, economic, market, policy, environmental and political perspectives. Due to the complex nature of risks and interdependencies, the method should have the capability to estimate interactions between risk factors and agents.
(iii) One of the reported barriers in SSA is the limitation in availability of market data [48,51]. In the absence of detailed data, a qualitative or semi-quantitative method is more appropriate to determine risk priorities
(iv) and assess the effectiveness of mitigations, thus ensuring a holistic approach.

Table 4 shows a comparison of methods with their capability to conform to the considerations set out above.

MCDA methods and cashflow analysis with MCS and SA have been widely used in other developing countries such as China for RE risk assessments. Apart from ANP, these methods are unable to model risk interactions. However, ANP has limitations in assessing effectiveness of mitigations which can be tested using ABM and SD.

SD provides an alternative to the reviewed methods because it can model interactions in a complex energy system. This feedback relationship can enable analysis of risk factors and the effect of their interactions. For example, it is possible to represent the circular effect of increased electrification on productivity and income, and subsequently the increased demand, which can lead to reduced revenue uncertainties and enhanced returns, leading to potentially more favourable investment decisions in the long term.

Although SD model development requires large data sets from both quantitative and qualitative sources, it has an advantage over ABM, which requires significantly more data in areas of model validation. SD was not used in the reviewed literature to assess social and political risks, possibly due to its limitation in representing social interactions; this can be complemented with ABM. ABM can be used to estimate behaviours of heterogenous agents acting independently. Such behaviours could be driven by socio-economic factors that impact revenue and investments. For instance, individual behaviour can be driven by socio-economic factors such as income seasonality, RE perceptions or availability of alternative traditional energy. These can drive demand variability, thus impacting revenue. Individual and investor behaviours can be modelled with ABM due to its capability to provide realism to modelling. ABM and SD methodologies have been combined to support policy analysis for grid systems. Zhao et al. [75] integrated SD into ABM framework to evaluate effectiveness of policy incentives to encourage PV systems adoption by incorporating consumer behaviour. The modelling framework comprised a 2- level simulation. On the higher level, the model is comprised of an ABM to simulate the customers' behaviour on adopting PV systems, while on the lower level, ABM and SD are employed to calculate the payback period of the PV system by different types of households [75]. ABM was used to simulate household consumption in the lower level, while SD was used to model the relationship between demand, PV generation, and local grid. The authors demonstrated that combination of the two techniques resulted in more realistic outcomes. A hybrid SD and ABM methodology for risk assessment and mitigation may thus offer more advantages when ABM is deployed to complement the SD gaps.

7. Conclusion

Decentralised RE systems have been identified as an enabler to improving energy access, meeting both SDG and climate change targets. Despite national targets, policy reforms and global trends of decreased capital cost, RE investments in SSA countries has been lower than required. Private investments have been identified as a key enabler to bridging the gap. However, there is a high-risk perception of investments in SSA which needs to be reduced to encourage investments [9,11].

This paper widens the scope of previous reviews of risk methods. Through a holistic lens, it provides a review of risk identification, analysis, evaluation, and mitigation methods for RE systems. It identifies the spatial and temporal distribution of studies carried out for developed, SSA and other developing countries. It is found that RE investment risks have been classified broadly according to barriers or uncertainties by focusing on location, stakeholders, or project phases. This paper has catalogued the various RE risks for developed and developing countries, including SSA based on standardised categorisation of risks (technical, economic, market, policy, social, resource, environmental, curtailment). Developing and developed countries face the same risk categories driven by different dimensions of factors. For example, social risk factors may include uncertainties in technology adoption and changes in societal attitudes in developed countries. In developing countries, these can result from resistance to change due to lack of awareness of RE benefits. It was also found that RE risk dimensions may differ according to geographical locations within the same country across national and local levels. Consequently, in providing impactful mitigations to improve risk profiles, it is necessary to consider distinct characteristics of locations across jurisdictional boundaries, e.g., national, state, local levels or based on demography, e.g., across urban, peri-urban, or rural locations.

Table 4
Comparative review of risk methods.

Application		Method	Literature reviews	MCDA		Cashflow/TE analysis		SD	ABM
		Criteria	***Interviews/surveys**	**Fuzzy ANP**	**Fuzzy AHP, IT2 Fuzzy DEMATEL**	**TE analysis and expert interview**	**TE or Cashflow analysis, SA and MCS**		
Risk Management	**Risk Identification**	Identify specific risks	•			•			
	Risk Analysis	Estimate probability and impact of risk	*•	•	•	•	•	•	
		Assess and estimate interaction between SSA risks factors:							
		Technical, Resource		•				•	•
		Economic, Finance, Market, curtailment		•				•	•
		Social		•					•
		Political		•				NS	•
		Policy/ regulatory		•				•	•
	Risk Evaluation	Quantify risk priority		•	•	•	•	•	•
	Risk Mitigation	**Estimate effectiveness of policy actions in mitigating investment risks factors**							
		Technical, Resource				•		•	•
		Economic, Finance Market				•		•	•
		Social							•
		Political						NS	NS
		Policy/ regulatory					•	•	•
Strengths			1. Relatively easy to implement	1. AHP, IT2 fuzzy & ANP are easy to understand and capable of using quantitative and qualitative data [62] 2. ANP allows for feedback and interaction for criteria [28,62].		1. Easy to understand and simplified		1. Models complex energy system from cause-effect perspective, rather than relying on statistically significant relationships [65]. 2. Lower amount of quantitative data needed for building a model compared to ABM [72].	1. Capability to model complex systems, host multiple actors and represent non-linear, social interactions, and RE adoption patterns [72]. 2. Allows for individual and non-optimal decision-making and simulates learning behaviour of agents [81].
Limitations			1. Generalised and may overlook context-specific factors. 2. Limited to risk identification unless combined with other methods	1. Apart from ANP, it does not allow for feedback or interaction between risks or criteria [30]. 2. Criteria, weights & values depend on subjective expert judgements [33]. 3. MCDA methods have not been used to determine mitigations.		1. Parameter changes are typically random and do not provide basis for decision making [80]. 2. MCS – variables need to be statistically independent to prevent result misinterpretation. Therefore, interactions and feedback relationships between variables cannot be modelled.		1. Does not represent social interactions within social networks [71]. 2. Long-term data is required for both model development and validation [71].	1. Significant amounts of empirical data are required to describe social interaction and for validation [31]. 2. Correct specification of realistic behaviour of agents is challenging [81].

This paper also introduces a conceptual framework that provides a holistic approach to risk management from identification, assessment to mitigation. The framework recognises that RE risks are complex involving multidisciplinary perspectives and their interactions with other risks, actors, and their actions. It proposes a structured means of identifying suitable actions. Actions such as policy mitigations may have side effects and interactions with actors and other policies, leading to unintended risk impacts. It, therefore, highlights the importance of analysing effectiveness of mitigations on risks and investment matrices given the interactions.

In the review of methods, it was found that risks were qualitatively identified primarily via literature reviews for SSA. This approach could be improved by combining literature reviews, surveys, expert interviews, and Delphi for specific locations and technologies.

RA and evaluation mainly employed semi-quantitative MCDA and SD methods for developing countries excluding SSA (where limited risk assessment studies were carried out). The reviewed methods assessed technical and economic risks at a minimum, while MCDA methods were additionally used to assess social, political and policy risks. Most MCDA had limitations in estimating interactions between risk factors. SD method was found to overcome this limitation due to its capability to conceptualise and model feedback relationships.

Qualitative methods have been used to identify risk mitigations. The effectiveness of policy actions in improving investments, meeting climate change and national targets have been tested using quantitative (ABM, MCS and SA) and semi-quantitative (SD) methods for policy, technical and economic uncertainties. SD has been largely employed in developing (excluding SSA) countries such as China and Taiwan. Its ability to represent investment risk's dynamic interactions and complexities make it a suitable tool for RA, evaluation, and mitigation. Its limitations in representing social interactions can be complemented with ABM. A hybrid SD-ABM method thus emerges as a powerful tool to analyse investment risks in developing countries such as SSA when applied within the framework of the ISO 31000 risk management guideline. This can provide a structured assessment of risks, identifying high priority risks and effective mitigations towards improving risk profiles. Such mitigations may include policy actions, policy implementation strategies, incentives, and investor actions, e.g., aggregating a spatially diverse portfolio of projects. Risk mitigations may incur associated costs which need to be weighed against the benefits. The hybrid model can be further enhanced by determining the cost-benefit of the risk mitigation using cashflow analysis and incorporating real options for investment decision making. The development of such a hybrid method can provide policymakers with a tool that can be used to test and tailor location-specific policies aimed at reducing investor risks and consequently improving energy access.

Credit author statement

Z.Y.I. Abba: Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration, Funding acquisition. N. Balta-Ozkan: Conceptualization, Methodology, Writing – review & editing, Supervision. P. Hart: Conceptualization, Writing – review & editing, Supervision.

Data availability

No datasets were generated or analysed during the current study.

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.

Acknowledgement

The authors thank the Petroleum Trust Development Fund (PTDF) Nigeria for supporting research through the PTDF scholarship programme.

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