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Adoption of green innovation technology to accelerate sustainable development among manufacturing industry

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A B S T R A C T

Recent advancements in green and innovative technologies have resulted in a number of innovations in manufacturing operations to accelerate sustainable development (SD). Despite several benefits of green innovation adoption (GIA), the adoption rate of these initiatives is still abysmal in manufacturing organisations. To fill this gap, we have developed and validated the GIA model grounded on the unified theory of acceptance and use of technology (UTAUT), which compels organisations to implement these novel technologies. Data was collected through a survey of 516 respondents from Pakistani manufacturing industries and analysed using structural equation modelling (SEM) and the artificial neural network (ANN) approach. The deliverables of SEM and ANN approaches demonstrated that all green integrated constructs of the research model, such as performance expectancy, effort expectancy, hedonic motivation, social influence, facilitating conditions, and innovation cost, predict green behavioural intention (GBI). Besides, GBI was found to have a strong direct and mediating effect among integrated constructs towards GIA. In addition, the moderation of organisational size highlighted the differentiation among small, medium and large size enterprises. Additionally, ANN specifies the robustness and relative importance of all integrated constructs, whereas green facilitating conditions have the highest relative importance value for GIA. The proposed integrated model offers novel insights for decision-makers and suggests various implications for adopting and implementing innovative green technologies to achieve SD objectives.
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Introduction

From the beginning of the 21st century, the transition and expansion of Information Technology (IT) have brought disruptive changes to all aspects of human life; it has advanced the methods of inception, production, and delivery of products and services (Guo et al., 2020; Hilkenmeier et al., 2021). The recent rise of the inculcation of novel digital manufacturing technologies and precision equipment into these processes has opened new doors of innovation in the production and delivery process (Guo et al., 2022). These new technologies have contributed to higher quality and increased value, reducing time to development and market and facilitating green manufacturing (Forcadell et al., 2021; Han & Chen, 2021). As green manufacturing fully respects the environmental impact and resource efficiency in production. The main features of green technologies are systematic, eco-prevention-focused, economic compliance, and enhanced effectiveness (Jansson, 2011; Skare & Riberio Soriano, 2021). During the last decade, sustainable development (SD) has gained substantial attention in the manufacturing industry due to increased awareness and perceived benefits for society of green technologies (Shahzad et al., 2020a).

Innovation, being the most critical driver for growth, propels a business towards excellence and guarantees a competitive advantage; it also enhances environmental efficiency, thus gaining help in raising the social capital necessary for future developments (Cillo et al., 2019). More and more organisations have adopted green innovation (GI) as a key component of their stratagem to mitigate the negative consequences of traditional growth models (Guo et al., 2020; Jahanshahi et al., 2020). For instance, the Chinese government has already integrated GI in Constitution 2018, laying the groundwork to promote a green technology bank for supporting green technology adoption (Hansen et al., 2018). Several nations have recently organised state-level financial institutions to promote SD and follow the "Green Industry Plan," i.e., Japan and Canada (Guo et al., 2020). These institutions can leverage public-private partnerships (PPPs) to

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facilitate green infrastructure and technological innovation (Yang et al., 2016). Further, GI enables organisations to manufacture eco-friendly products by minimising resource utilisation and wastage to accomplish SD (Khan et al., 2021; Shin et al., 2022). Scholars such as Fernando et al. (2019) and Shahzad et al. (2020b) have recommended GI as a significant driver for SD by emphasising that green processes and green products provide similar value to consumers with minimal social and environmental impacts (Awan et al., 2020). After identifying the key benefits of GI, various stakeholders pressured for its adoption and implementation (Shahzad et al., 2022; Shahzad et al., 2020a). Though radical change is obligatory at the ecological, cultural, and social levels, organisations have to play their certain role in SD (Khan et al., 2021). However, green innovation adoption (GIA) faces significant challenges in achieving SD in manufacturing organisations due to various decision-making factors.

With rising commodity prices and concerns regarding sustainable sourcing, organisations may prefer to use the latest innovative and environment-friendly technologies to minimise waste and costs, which can be helpful in attaining competitive advantage (Ahn et al., 2016; Anser et al., 2020). However, there are no specific criteria for categorising green technology adoption globally (Skare & Riberio Soriano, 2021). There are still many concerns regarding adopting green and novel technologies, e.g. financial barriers, environmental policies, market demand, knowledge, and awareness (Awan et al., 2020; Forcadell et al., 2021; Guo et al., 2020). From a budgetary perspective, purchasing the necessary precision tools and expertise could signify a large proportion of organisational expenditure; therefore, organisations must be confident about the feasibility of such investments (Guo et al., 2020).

Green and environmental policies and initiatives are thought to increase corporate success only if implemented across the board, with confirmation and support by all partners. Research has demonstrated that a lack of customer engagement and recognition will lead to a loss of investment and resources (Li et al., 2020). More recently, Ahmad et al. (2021) identified that overdependence on coal energy is the primary source of hazardous emissions; improved energy efficiency can reduce it through green technological innovation and green initiatives. Therefore, it is critical for organisations to evaluate the social, economic and environmental aspects of green technologies (Anser et al., 2020; Shahzad et al., 2021). Being the seventh most susceptible nation to climate change, Pakistan should seek sustainable and green technological solutions (J. Lee et al., 2021); it is regarded as one of the least innovative countries with a poor ranking in Asia as well as in the world (Global Innovation Index, 2018). Due to poor air quality, the famous industrial city Lahore was declared the most polluted in the world recently. To overcome these environmental problems and consider SD, the current leadership of Pakistan implemented stringent environmental laws to protect the environmental deterioration and tried to facilitate the organisations to lessen their dependency on fossil fuels and exploit renewable energy resources. As stringency in environmental strategies, environmental tax, and reduced hazardous emissions positively affects GI (Maasoumi et al., 2020). However, resources of renewable energy are also limited. Research on developing nations such as Pakistan may offer clearer views of how GIA policies might control environmental destruction and transform eco-friendly goods that avoid environmental pollution and diminish industrial waste.

Extant literature on the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) identified various factors, e.g. performance and effort expectancy, facilitating conditions, and social influence, as the essential drivers influencing technology adoption (see Appendix A) (Jun et al., 2021; Venkatesh et al., 2003). After developing the UTAUT2 model, researchers also recognised the importance of hedonic motivation and innovation cost for green technology adoption (Ahn et al., 2016; Anser et al., 2020; Venkatesh et al., 2012). These attributes strongly affect green behavioural intention (GBI) (J. Lee et al., 2021; Wang et al., 2020). Although it can be argued that GIA is comparable to that of other technologies, several scholars endorse that the implementation and conditions of different technologies will diverge significantly, resulting in variations in adoption factors depending on the technology type (Song et al., 2019; Tseng et al., 2018). Therefore, for a business to successfully introduce a green technological initiative into its operations, it must comprehend which factors will increase social acceptance among the stakeholders. Hence, there is a real need to critically investigate the implementation issues and adoption concerns by analysing these GIA challenges. The problems stated above and the literature gap compelled this investigation to ask these research questions:

- How do green decision-making factors impact green behavioural intention to adopt green innovation technologies?
- Does green behavioural intention mediate the relations among integrated constructs and green innovation adoption?
- How does the boundary factor of organisational size influence the relations of proposed constructs?

This research aims to provide various contributions to the literature. This is the first study that offers multiple constructs of the UTAUT in the context of a green and sustainable environment. Previously no any study employed these constructs in the context of green technologies adoption. Second, to gain a holistic understanding of the decision-making factors of UTAUT, the direct and indirect effects of these factors on both GBI and GIA were validated through structural equation modelling (SEM) and the artificial neural network (ANN) approach. These factors were considered critical indicators for technological adoption (Xie et al., 2022; Venkatesh et al., 2012; Ahn et al., 2016). Existing studies reported inconclusive outcomes; by employing novel SEM and ANN approaches current study provides a comprehensive conclusion for GIA. Third, assessing the moderating role of organisational size was helpful in evaluating initial confidence in green technology characteristics. Larger organisations are more resourceful and have a greater probability of adopting green initiatives and integrating technological changes more quickly. Lastly, this research provides several implications for a developing country such as Pakistan due to its vulnerability to global environmental changes and less coverage in prior literature; it demonstrates GIA's relevance in routine manoeuvres and elucidates how organisations can advance their SD. The review of related literature is described in the following parts, followed by methodology, results, and conclusions, and finally, the study is concluded with future recommendations.

Literature review & hypotheses development

Green innovation

GI provides organisations with the chance to diminish their operations' adverse effects on the environment and guarantees a competitive advantage (Awan et al., 2020). It can facilitate the development of new manufacturing processes and products that are less injurious to the ecosystem and natural environment (Khan et al., 2021). GI is "the production, application or exploitation of a good, service, process, organisational structure or management or business method that is novel to the firm and results in a reduction of environmental risk" (Ma et al., 2018). The definition of GI has various forms, e.g. green technological innovation, which encompasses product and process innovation, and green non-technological innovation comprising management innovation and organisational structure (Chang & Chen, 2013; Chen et al., 2006; Hilkenmeier et al., 2021). The former aims to assimilate various advanced and novel technologies that can improve the existing process and products to reduce energy consumption, prevent pollution and save natural resources (Fernando et al., 2019; Khan et al., 2021; Xie et al., 2022). It also alludes to process and product innovation. The latter encompasses adopting/restructuring firms' management strategies, i.e. environment, energy, quality management, green supply chain, and green marketing to minimise harmful environmental effects (Klein et al., 2021; Shu et al., 2016).

Chen et al. (2006) describe GI as "hardware or software innovation that is related to green products or processes, including the innovation in technologies that are involved in energy saving, pollution prevention, waste recycling, green product designs, or corporate environmental management." It is positioned as the main driver of long-term socio-economic progress. Several studies acknowledged the key factors that affect GI adoption, e.g. concerned stakeholders' pressure, strategic orientation, organisational learning, knowledge management, absorptive capacity, and consumers' demands (Awan et al., 2020; Dangelico, 2017; Klein et al., 2021; Shahzad et al., 2020a; Song et al., 2020). Further, organisational innovation is a driving force in enhancing industrial export, environmental performance, and, eventually, business excellence and SD (Li et al., 2020; Wu et al., 2019). In brief, GI inclines to improve competitiveness by developing innovative goods, processes, materials, and institutional frameworks.

Green innovation adoption and UTAUT

With increased environmental deterioration and climate change envisaged by rising hazardous emissions and pollution, global sustainable economy is certainly constrained (Khan et al., 2021). Green technologies and monitoring policies are imperative to regulate and encourage GIA (Li et al., 2020). GIA requires innovative organisational strategies to switch their classical and traditional means of production to novel and sustainable operations (Anser et al., 2020). Nevertheless, transformation into sustainable operations remains difficult for organisations because multiple uncertainties and complexities are involved in the transformation procedure (Han & Chen, 2021). Different sectors have accepted and transformed their operations into green operations following SD indicators, e.g. environmental, social, and economic performance (Jahanshahi et al., 2020). GIA in businesses has also attracted experts' and researchers' attention (Forcadell et al., 2021; Han & Chen, 2021; Klein et al., 2021). Recently scholars have identified different barriers and enablers for GIA in manufacturing enterprises (Han & Chen, 2021). From prior literature, the adoption of green technology, or its acceptability, can be recapitulated as the extent of the possibility of an emerging novel technology being authorised by groups or individuals (Awan et al., 2020; Jahanshahi et al., 2020).

Many scholars modelled the critical elements of technology adoption for better decision-making, which is further developed in the UTAUT model, and verified the rationality of their attributes (Venkatesh et al., 2003). To anticipate technology adoption intention and usage of novel and innovative technologies, the UTAUT prolongs the TAM, the theory of reasoned action (TRA), diffusion of innovation theory, and a mirror of cognition theory (Zhao & Bacao, 2020). The UTAUT comprises four fundamental driving factors of intention and usage: performance and effort expectancy, facilitating conditions, and social influence (Venkatesh et al., 2003). Various studies integrated the UTAUT to explore behavioural intention to accept the latest technologies, stimulating its generalizability (Anser et al., 2020; Zhao & Bacao, 2020). The UTAUT framework is the foremost consolidated model, comprehensively describing technology adoption (Al-Saedi et al., 2020). This model was further studied by integrating others factors such as compatibleness expectancy, sustainable innovativeness, and environmentalism, in adopting green household technology (Ahn et al., 2016). Accordingly, knowledge of green products influences users' behaviour to care for the natural environment following the UTAUT model as knowledge influences all phases of the purchasing decision process (Hsu et al., 2017).

Despite these four fundamental variables, Venkatesh et al. (2012) underlined the need to integrate more relevant prognosticator variables to forecast behavioural intentions for the technology adoption perspective by modifying the UTAUT to provide a new predicting model, namely UTAUT2. This latest model has progressively been implemented for investigating multiple queries such as self-service technology, adoption of mobile technology, mobile banking and commerce, online education, and online healthcare services (Huang & Kao, 2015). Hedonic motivation and cost of innovation are considered more important factors of UTAUT2, which are further integrated into the research framework of this study to emphasise efficacy and utility. Moreover, Ma et al. (2017) established that, compared to non-labelled items, the sustainable label reading behaviour of products increases the purchasing of sustainable and green products, while the increasing ecological cognisance among individuals (Chen, 2008) suggests that they are eager to pay a greater value for eco-friendly goods. Since this study's primary aim is to discover the factors that influence GIA, the UTAUT2 model can offer better insights; therefore, it is employed as the research framework, as shown in Fig. 1.

Green performance expectancy (GPE)

Performance expectancy is a key variable of the UTAUT model, which influences behavioural intentions. It is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). It comprises four fundamental measures that gauge performance: perceived usefulness, job fit, extrinsic motivation, and comparative edge (Huang &

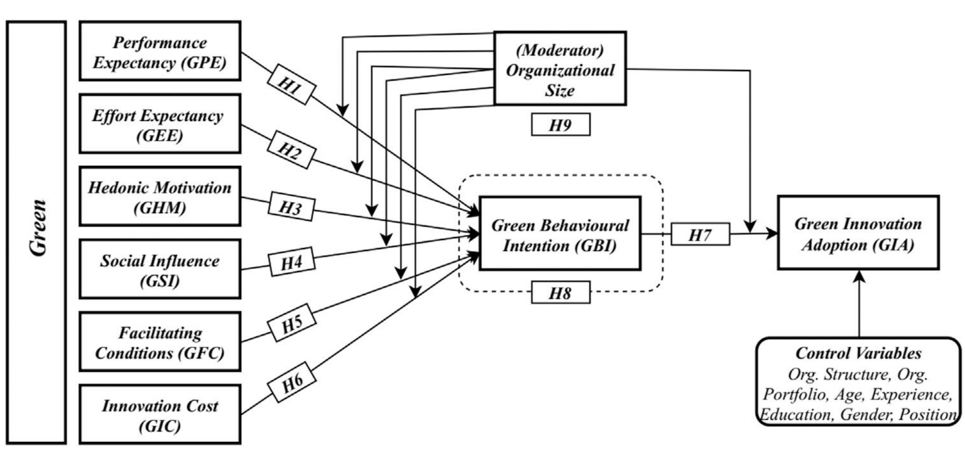

Fig. 1. Research model.

Kao, 2015). It is the most significant contributor to identify individual intention to accept new technology and satisfaction (Zhao & Bacao, 2020). Prior studies have certified that performance expectancy positively and considerably affects adoption and continuing usage of the latest technologies, i.e., mobile banking. In the setting of this study, GPE may have a considerable impact on GBI, as various green factors such as supplier selection, procurement, industrial engineering and consumerism all have a considerable impact on green purchase intention (Anser et al., 2020). Recent studies specified that green product knowledge positively affects individual green behaviour (e.g. Hsu et al., 2017). Thus, the subsequent hypothesis is proposed:

H1: Green performance expectancy positively affects green behavioural intention.

Green effort expectancy (GEP)

Effort expectancy is one of the dominant constructs of UTAUT, described as "the degree of ease of use associated with the usage of a new technology or a technology product" (Huang & Kao, 2015). It is a comparable construct with ease or complexity of use (Zhao & Bacao, 2020); the latter are identified as the extent to which innovative technology is complex or easy to use and comprehend. The complexity of innovative technology may harm its adoption (Dangelico, 2017). It is expected that the larger the ease of use of innovative technology, the lower the individual behavioural intention (Al-Saedi et al., 2020). Some research studies found that effort expectancy harms using novel technologies, i.e., internet banking and shopping online (Chopdar and Sivakumar, 2019). The latest studies identified that effort expectancy significantly affects innovative technologies' utilisation and satisfaction by employing and validating the UTAUT model (Anser et al., 2020; Shang & Wu, 2017). Further, for our study context, green product labelling enhances the individual green behaviour and intention to utilise sustainable and green products compared to non-labelled products (Ma et al., 2017). Accordingly, the subsequent hypothesis is proposed:

H2: Green effort expectancy positively affects green behavioural intention.

Green hedonic motivation (GHM)

Hedonic motivation, known as perceived enjoyment, refers to internal pleasure, fun, or satisfaction experienced using the latest innovative technology and articulates a key role in contributing to the UTAUT2 model (Tam et al., 2020). An individual with utilitarian motivation focuses on instrumental values, while one with hedonic motivation focuses on fun and pleasure (Wang et al., 2020). It has been demonstrated to be a more fundamental driver than other UTAUT components and a core estimator of behavioural intention (Venkatesh et al., 2012). Empirical research identified that hedonic motivation affects technology adoption both in individual and organisational contexts (Ashfaq et al., 2021; Huang & Kao, 2015). In the context of GHM, users' hedonic motivation captures a vital role in predicting green buying behaviour (Choi & Johnson, 2019). Prior studies acknowledge that individuals' thinking and green motivation incite their urge to purchase eco-friendly and green products (Ali et al., 2020). Motivation for adopting smart technologies is a pertinent factor that affects individuals' intentions to enhance their households' sustainability and sustainable consumption behaviour (Ahn et al., 2016). Furthermore, individuals' novelty-seeking behaviour and green consumerism also impact green purchase intention (Anser et al., 2020; Choi & Johnson, 2019). Thus, subsequent to the above discussion, we posit the below hypothesis:

H3: Green hedonic motivation positively affects green behavioural intention.

Green social influence (GSI)

Social influence means that social networks incline individuals' decisions since they frequently evaluate the ideas and opinions of others when deciding whether or not to espouse innovative technologies (Anser et al., 2020). It is described as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). It denotes encompassing the individual decision-making process to accept innovative technology affected by others' opinions (Ashfaq et al., 2021; Dangelico, 2017). Social influence is also considered a subjective norm in TAM and social norms in TRA (Zhao & Bacao, 2020). Recent research identified that social influence significantly influences the adoption of innovative technologies and behavioural intention at all points in time (Wang et al., 2020). In this research setting, prior studies identified that social influence related to environmental conservation is the most influential element in predicting and adopting green technology (Ahn et al., 2016). Moreover, it helps shape individual behaviour towards green intentions and sustainable purchase decisions, e.g. purchasing unique biodegradable packaging and carrying bags (Choi & Johnson, 2019). The greater the social influence of green technology adoption, the greater the individual's persistence in using it. As a result, the following hypothesis is advanced:

H4: Green social influence positively affects green behavioural intention.

Green facilitating conditions (GFC)

Facilitating conditions are the final and central element of the UTAUT model. Facilitating conditions are "the factors in an environment that hinder or make an activity easier to perform for an individual" (Venkatesh et al., 2003). Individual-level and group-level are the two forms of facilitating conditions. The former is about the individual insight into environmental support; the latter is about organisational support available for groups (Ahn et al., 2016). Without a comprehensive set of facilitating conditions, it is challenging to adopt and use the latest technology. However, it is rational in a green context since the facilitating conditions, e.g. training and guidance about innovative and green technology (software and hardware), persuade usage and GBI (Tariq et al., 2016). The prospective barriers to use can be eliminated or reduced significantly (Venkatesh et al., 2012). Prior literature identified that organisations' employees would accept and adopt new technology when they received support and facilitating assistance (Tam et al., 2020). Nysveen and Pedersen (2016) identified that an individual with accession to a conducive series of facilitating conditions is expected to adapt and accept new technology. Wong (2013) suggested that adoption of green technologies enables organisations to reduce adverse ecological impact, facilitating SD outcomes. So, the following hypothesis is proposed:

H5: Green facilitating conditions positively affect green behavioural intention.

Green innovation cost (GIC)

Innovation cost is another of the most critical variables in the UTAUT2 model, as product cost significantly influences technology adoption (Tam et al., 2020). The price value is conventionally specified as arbitration between cost and benefit analysis. When the advantages of adopting new technology are superior to the financial costs, the innovation cost shows positive results and positively influences adoption intention (Venkatesh et al., 2012). Besides, GI is not free; however, it is lucrative for organisations in the long run (Zailani et al., 2015). Prior research acknowledged that environmental compliance is an extra financial burden and increases production costs instead of considering it an essential strategy to avert harmful ecological effects (Liu et al., 2021). However, the number of environmentally conscious consumers is rising; they prefer to use eco-friendly products (Chang & Chen, 2013). They desire innovative and green products and are determined to pay a greater price for green items (Chen, 2008). Further, Wei et al. (2018) stated that less environmental motivated consumers are likely to pay less for green products. However, highly environmental motivated consumers are likely to pay high. Green processes and product innovation diminish adverse ecological impacts and enhance production efficiency and sustainable financial performance through cost and waste minimisation (Zailani et al., 2015). Prior studies show contradictory arguments regarding this relationship, so re-investigation of this relationship is indispensable. Thus, the subsequent hypothesis is proposed:

H6: Green innovation cost positively affects green behavioural intention.

Green behavioural intention (GBI)

Psychologists and social scientists acknowledge that behavioural intentions always strongly affect actual behaviour (Straub, 2009; Zafar et al., 2020). Nevertheless, the prediction of actual behaviour is still challenging. Behavioural intention denotes "the degree to which a person has formulated conscious plans to perform or not perform some specified future behaviour(s)" (Huang & Kao, 2015). The prior researcher, Venkatesh et al. (2012) identified that behavioural intention regarding technology adoption plays a magnificent role in actual technology adoption. Several researchers employ intention behaviour as a surrogate of actual adoption behaviour (Karampournioti and Wiedmann, 2022; Zafar et al., 2020). GI is now growing a competitive strategy due to increasing environmental regulations and optimal sustainability outcomes. Further, GIA is a long-run effort that necessitates an organisation to create substantial developments in processes and products, which inevitably invoke environmental risks (Jahanshahi et al., 2020; K. Lee et al., 2021). Larger organisations are ready to assimilate innovative technologies, capabilities, and external and internal environments; they are more likely to put potential risks beneath control (Albino et al., 2009). Thus, consistent with the underlying theory and research model, we expect that GBI will substantially influence GIA. Hence, we propose the following hypothesis:

H7: Green behavioural intention positively affects green innovation adoption.

Mediating influence of GBI

This research seeks to determine whether GBI acts as a mediator among diverse decision-making factors of UTAUT and green innovation adoption. Behavioural intention focuses on the desire to actual usage or adoption; such desires can be dominant and irresistible; still, it does not basically ascertain the actions. Several studies provided the theoretical background and critical role of behaviour intentions for actual technology adoption (Ashfaq et al., 2021; Ifedayo et al., 2021; Venkatesh et al., 2012). Ifedayo et al. (2021) identified behaviour intentions as a prognosticator of podcast technology acceptance in Nigeria directly and indirectly as well. Further, J. Lee et al. (2021) also acknowledged that eco-friendly behavioural intentions significantly influence the adoption decisions regarding electric vehicles. The previous scholars have extensively conferred how green thinking and motivation relate to green behaviour and adoption intention (Ali et al., 2020; Choi & Johnson, 2019). Moreover, Casey and Wilson-Evered (2012) also emphasise the key mediating role of behavioural intention among performance expectancy, effort expectancy, and trust in new technology. Therefore, based on the extant literature, we propose that GBI plays a mediating role among integrated constructs and GIA. Thus, the following hypotheses are proposed.

Green behavioural intention mediates the relation among green performance expectancy **(H8a)**, green effort expectancy **(H8b)**, green hedonic motivation **(H8c)**, green social influence **(H8d)**, green facilitating conditions **(H8e)**, and green innovation cost **(H8f)** to green innovation adoption.

Moderating influence of organisational size

Generally, the number of employees at any particular geographical location is known as organisational size. Several researchers have identified that organisational characteristics have a higher propensity for the behavioural intention to adopt innovative technologies (Aibar-Guzmán et al., 2022). Following previous studies, this research also considers organisational size as moderating variable (Ma et al., 2018; Shu et al., 2016). Lin and Ho (2008) emphasised that organisational resources, including quality of resources and organisational size, further influence the adoption of new green technology. Further, Lin et al. (2020) highlighted that organisational resources significantly affect green technology adoption. More resourceful and larger organisations have higher chances of adopting and integrating technological changes into their operations, as this is a lengthy process and needs massive investment. Organisations can implement an advanced environmental strategy by adopting green technologies; when the organisation has higher resources and greater size, the adoption capacity of innovative technologies is higher. So, the following hypothesis is proposed:

H9: Organisational size significantly moderates the aforementioned relations towards green behavioural intention and green innovation adoption in confounding ways.

Research methodology

Measures

A questionnaire survey comprised of two portions was adopted to gather data. The first portion is associated with the demographic evidence of respondents and organisations (see Table 1). The second consists of different measures related to targeted variables. The employed instrument is adopted from prior studies with multiple validated and reliable items. All measurements were concluded following the endorsements of a panel included of three professors and professionals to ensure face validity. GPE, GEE, GSI, GFC, and GBI were evaluated by four, four, three, five, and three items, respectively (Venkatesh et al., 2003); GHM, GIC, and GIA were assessed using four, four, and six items, respectively (Venkatesh et al., 2012). All items were answered on a seven-point Likert scale "1=strongly disagree" to "7=strongly agree". Before conducting the formal survey, pilot testing was undertaken to ensure content validity, but few modifications were necessary to certify data validity and reliability.

Data collection

Analysis of this investigation was based on quantitative data collected via a questionnaire from various manufacturing industries in one of the emerging markets, i.e., Pakistan, between November 2021 and March 2022. The current government establishes stringent environmental regulations to reduce dependence on coal energy and shift manufacturing to renewable energy sources. However, renewable

Table 1
Demographic details.

Particulars (N=516)		Frequency	Percentage
Gender	Male	310	0.60
	Female	206	0.40
Age (years)	18 to 25	145	0.28
	26 to 35	224	0.43
	36 to 45	81	0.16
	46 to 55	43	0.08
	Above 55	23	0.04
Experience (years)	Less than 1	111	0.22
	1 to 3	194	0.38
	4 to 7	128	0.25
	8 to 10	62	0.12
	Above 10	21	0.04
Education	Master's	121	0.23
	Bachelor's	178	0.34
	Intermediate	101	0.20
	Matric	91	0.18
	Others	25	0.05
Job Position	Office Executives	116	0.22
	Supervisors	165	0.32
	Assistant Managers	103	0.20
	Managers/ Sr. Manager	74	0.14
	CEO /Directors	58	0.11
Org. Size (emp)	Less than 100	80	0.15
	101 to 150	81	0.15
	151 to 200	85	0.16
	201 to 250	97	0.18
	251 to 300	64	0.12
	Above 300	109	0.21
Org. Structure	Line	30	0.06
	Line and Staff	105	0.20
	Functional	135	0.26
	Divisional	52	0.10
	Matrix	49	0.09
Org. Portfolio	Single Product Local	70	0.14
	Multi-Product Local	160	0.31
	Single Product Global	248	0.48
	Multi-Product Global	38	0.07

energy resources are also limited. So, it needs to take some corrective measures to promote green initiatives in the current challenging environment. Similarly, it faces various SD issues requiring vigorous green product development and process innovation (Awan et al., 2020). Therefore, Pakistan has been identified as an appropriate context for evaluating our research hypotheses. The questionnaires were distributed online using Google docs and WhatsApp and offline through personal visits including a cover letter illustrating the aim of this research and assuring respondents' data confidentiality. Due to the epidemic, we conveniently contacted upper, middle, and front-level staff members to obtain higher responses from different manufacturing industries, including textiles and clothing, petroleum and chemicals, electronics and IT, food and beverages, metal manufacturing, and leather products.

To enhance the response rate, reminders and follow-ups were sent to concerned respondents. These corporations were listed in the "Pakistan Stock Exchange (PSX)" and registered with the "Securities and Exchange Commission of Pakistan (SECP)." 980 questionnaires were dispersed to 399 manufacturing units in Pakistan; we received 516 functional responses – a response rate of 52%. These respondents signify the organisation as a whole. Usually, in survey studies, scholars have a low response rate due to respondents' busy schedules and non-access to the internet (Hair et al., 2017). Due to the pandemic, many employees were working from home and had easy access to the internet, so we had a higher response rate than usual. Also, a large sample leads to more precise estimation and results (Asiamah et al., 2017). The majority of respondents held supervisory positions, i.e., 45%, responsible for executing organisational strategies and implementing policies; 60% were male, and the majority were aged between 18 and 35. (see Table 1). The current research adopted a 10X rule for sample size as guided by Hair et al. (2017), which is "10 times the largest number of structural paths directed at a particular latent construct in a structural model". The sample size was derived through G*Power software proposed by Prajapati et al. (2010) to ensure the sample's adequacy for the research model. A set of power analyses revealed that our sample is suitable for further investigation.

Common-method bias variance

Common method bias (CMB) variance is specified as "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Cohen, 1988). It is argued to be a main concern in the questionnaire survey. Initially, CMB was estimated using Harman's single factor, where the first factor has a cut-off value of less than 50% (i.e., 31.15%) (Harman, 1976). Besides, a more rigorous method for testing CMB vis full collinearity evaluation was also implemented (Kock, 2015). The resulting variance inflation factor (VIF) values were less than 3.3 (Kock, 2015). These findings imply that CMB is unlikely to cause severe concern.

Results

PLS-SEM and ANN were utilised for this study, and the data were analysed by SmartPLS (ver. 3.2.8) and IBM SPSS statistics (ver. 25). PLS-SEM is highly recommended when an investigation is exploratory and intends to predict (Hair et al., 2017). Normal distribution is not a precondition of PLS-SEM compared to other methodologies, and it can work with a small sample. PLS-SEM has the potential to measure all causal relationships concurrently and can test a complex model without the removal of any model variable. These conditions are suitable for employing the PLS-SEM methodology (Hair et al., 2017). Besides, ANN is more robust and proficient in recognising both linear and non-linear relations and outperform classical regression investigations, e.g. multiple regression analyses (Sim et al., 2014). Though, it suffers from the shortcoming of a "black box" operation algorithm and is therefore not appropriate for testing hypotheses. Thus, we employed PLS-SEM for hypotheses testing and ANN for evaluating the relative importance of variables. Model is measured according to Hair et al. (2017) in two steps: (outer) measurement and (inner) structural model.

Analysis of measurement model

The construct reliability method ("Cronbach's alpha (CA), rho_A, and composite reliability (CR)") and validity ("discriminant and convergent validity") was used to estimate the measurement model by following Hair et al. (2017). Referring to the results in Table 2, the CA score ranges from 0.741 to 0.841, whereas the figures of rho_A are in the range of 0.742 and 0.842, and the statistics of CR squeeze a range from 0.853 to 0.889. All statistics are greater than the threshold of 0.70; subsequently, the construct reliability is established (Cohen, 1988; Hair et al., 2017). The loading of factors and "Average Variance Extracted (AVE)" were assessed to determine the convergent validity (CV). These statistics were also larger than the threshold of 0.50, as Hair et al. (2017) advised. The resulting statistics authorised the CV of variables.

Furthermore, the discriminant validity (DV) is affirmed using a traditional but vastly familiar approach (Fornell & Larcker, 1981) and a recent and latest approach heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). In the first approach, the square root of AVE should be larger than the correlation among targeted components. The second HTMT approach acclaims a cut-off value of 0.85 (Sarstedt et al., 2017). The findings in Tables 3 and 4 approve both criteria of DV.

Table 2
Reliability and validity.

Constructs	Factor Loadings	CA	rho_A	CR	AVE
Green Effort Expectancy (GEE)		0.741	0.744	0.838	0.564
GEE1	0.804				
GEE2	0.735				
GEE3	0.749				
GEE4	0.713				
Green Facilitating Conditions (GFC)		0.841	0.842	0.887	0.612
GFC1	0.748				
GFC2	0.801				
GFC3	0.813				
GFC4	0.805				
GFC5	0.741				
Green Behavioural Intention (GBI)		0.742	0.742	0.853	0.659
GBI1	0.800				
GBI2	0.814				
GBI3	0.821				
Green Innovation Adoption (GIA)		0.808	0.826	0.865	0.563
GIA1	0.741				
GIA2	0.749				
GIA3	0.706				
GIA4	0.803				
GIA5	0.751				
GIA6	0.762				
Green Hedonic Motivation (GHM)		0.803	0.804	0.871	0.629
GHM1	0.777				
GHM2	0.802				
GHM3	0.828				
GHM4	0.764				
Green Innovation Cost (GIC)		0.755	0.758	0.845	0.576
GIC1	0.747				
GIC2	0.780				
GIC3	0.765				
GIC4	0.744				
Green Performance Expectancy (GPE)		0.771	0.772	0.854	0.593
GPE1	0.792				
GPE2	0.780				
GPE3	0.752				
GPE4	0.755				
Green Social Influence (GSI)		0.814	0.821	0.889	0.728
GSI1	0.820				
GSI2	0.878				
GSI3	0.861				

Analysis of structural model

Following the validation of the outer model, the structural model was evaluated in order to test the hypotheses. To determine the relevance of the hypotheses, a bootstrapping approach was used (5000 resample). The findings of the model disclosed a significant and positive effect of GPE *(H1: βeta value=0.182; p<0.001)*, GEE *(H2: βeta value=0.138; p<0.002)*, GHM *(H3: βeta value=0.154; p<0.001)*, GSI *(H4: βeta value=0.123; p<0.033)*, GFC *(H5: βeta value=0.212; p<0.001)*, and GIC *(H6: βeta value=0.157; p<0.001)* on GBI which support the hypotheses H1 to H6 respectively. Furthermore, hypothesis H7 revealed a significant and positive influence of GBI on GIA *(H7: βeta value=0.247; p<0.000)*. The result of control variables revealed that these were insignificant. The overall outcomes of the hypotheses are provided in Table 5.

Table 3
Discriminant validity (Fornell-Larcker Criterion).

	GEE	GFC	GBI	GIA	GHM	GIC	GPE	GSI
GEE	*0.751*							
GFC	0.556	*0.782*						
GBI	0.522	0.563	*0.812*					
GIA	0.113	0.107	0.247	*0.750*				
GHM	0.311	0.325	0.510	0.322	*0.793*			
GIC	0.488	0.476	0.582	0.281	0.577	*0.759*		
GPE	0.418	0.450	0.552	0.269	0.458	0.503	*0.770*	
GSI	0.531	0.554	0.598	0.253	0.565	0.624	0.544	*0.854*

Table 4
Discriminant validity (HTMT).

	GEE	GFC	GBI	GIA	GHM	GIC	GPE	GSI
GEE								
GFC	0.700							
GBI	0.702	0.712						
GIA	0.161	0.133	0.309					
GHM	0.404	0.395	0.660	0.396				
GIC	0.652	0.596	0.774	0.360	0.746			
GPE	0.554	0.555	0.727	0.332	0.581	0.664		
GSI	0.681	0.668	0.767	0.312	0.699	0.798	0.685	

Mediation analysis

The mediating impact of the GBI was evaluated by the series of steps (Nitzl et al., 2016). At first, this study inspected the indirect effect of the GPE, GEE, GHM, GSI, GFC, and GIC to GIA through GBI; and found a significant effect of these variables with βeta values 0.043, 0.033, 0.038, 0.031, 0.50, 0.037, respectively. In the next step, the direct effect of GPE, GEE, GHM, GSI, GFC, and GIC was measured without removing the mediator (GBI). A significant positive outcome of these variables with βeta values 0.182, 0.138, 0.154, 0.123, 0.212, and 0.157 were found respectively. The results are specified in Table 5, which leads to partial mediation. Besides, this study noticed the sign of indirect and direct effects and found positive and in the same direction; therefore, it might be determined that the GBI has complementary partial mediation (Hair et al., 2017). Hence, H8a to H8f is fully supported.

Multi-group analysis for moderation

The moderation effects of organisational size were estimated through the multi-group analysis (MGA) technique. MGA assists in estimating the significant difference among various groups in data for an identical model; predominantly when a categorical moderator is involved (Hair et al., 2017). As the organisational size is a categorical moderator, to assess its moderating effect, data were divided into three groups according to the number of employees (Less than 150-small, n=161), (151 to 250-medium, n=182), and (More than 250-Large, n=173). Results of MGA in Table 6 revealed a significant difference in GIA levels observed among these three groups. In the case of smaller organisations, the effect of GEE, GSI, and GIC on GBI was insignificant. For medium-size organisations, the impact of GHM and GSI on GBI was insignificant, whereas for larger organisations, the effect of GSI on GBI was insignificant only, still it is significant at 10% level of significance. These results suggested that the propensity for GIA among these groups has discrepancies (smaller to larger). Smaller organisations have limited resources and portfolios, so they have a

Table 5
Hypotheses testing.

	Key Relationship Paths	β Values	T- Values	P-Values	Decision
H1	GPE -> GBI	0.182	4.131	0.000	Supported
H2	GEE -> GBI	0.138	3.126	0.002	Supported
H3	GHM -> GBI	0.154	3.306	0.001	Supported
H4	GSI -> GBI	0.123	2.127	0.033	Supported
H5	GFC -> GBI	0.212	3.314	0.001	Supported
H6	GIC -> GBI	0.157	3.184	0.001	Supported
H7	GBI -> GIA	0.247	5.776	0.000	Supported
Mediation Analysis (Indirect Effects)					
H8a	GPE -> GBI -> GIA	0.043	3.049	0.002	Supported
H8b	GEE -> GBI -> GIA	0.033	2.534	0.011	(Complementary
H8c	GHM -> GBI -> GIA	0.038	2.838	0.005	Partial Mediation)
H8d	GSI -> GBI -> GIA	0.031	1.978	0.040	
H8e	GFC -> GBI -> GIA	0.050	3.108	0.002	
H8f	GIC -> GBI -> GIA	0.037	2.493	0.013	

Table 6
MGA for moderation.

Relationship Paths	β Values (Large)	T-Value	β Values (Medium)	T-Value	β Values (Small)	T-Value
GPE -> GBI	0.164	2.193	0.172	2.592	0.201	2.329
GEE -> GBI	0.184	2.745	0.285	4.204	0.045	0.606
GHM -> GBI	0.156	1.964	0.109	1.621	0.222	2.665
GSI -> GBI	0.180	1.890	0.087	0.973	0.034	0.316
GFC -> GBI	0.318	3.231	0.194	2.731	0.404	3.816
GIC -> GBI	0.239	2.046	0.207	3.429	0.091	1.028
GBI -> GIA	0.217	3.232	0.270	4.663	0.307	4.650

Table 7
R^2, Q^2 and effect size.

Endogenous variables	R^2	Q^2	Exogenous variables	F^2
Green Behavioural Intention	0.536	0.345	Green Performance Expectancy	0.044
Green Innovation Adoption	0.061	0.031	Green Effort Expectancy	0.024
			Green Hedonic Motivation	0.030
			Green Social Influence	0.014
			Green Facilitating Conditions	0.055
			Green Innovation Cost	0.026
			Green Behavioural Intention	0.065

low GI adoption level, unlike medium and large-size organisations. Hence, H9 is fully supported.

Goodness of fit (GOF) indexes

The model fit was established by a largely adequate method, i.e. "standardised root mean square residual" (SRMR), where the SRMR value should be less than 0.08 (Hair et al., 2017). The outcomes revealed the value of SRMR is 0.065, suggesting our model is quite well. Secondly, we also calculated GOF using the formula (GOF=$\sqrt{(AVE \times R^2)}$) (Wetzels et al., 2009). In our model, the GOF is 0.429, demonstrating the model fulfils the large criteria. Besides R^2 (coefficient of determinants), F^2 (effect size) and Q^2 (predictive relevance) were also analysed. The resultant values were in good range and provided in Table 7.

Robustness check through the artificial neural network (ANN) approach

Following prior social scientists (Chavoshi & Hamidi, 2019; Zafar et al., 2021), this study also employed ANN to identify each variable's relative importance and reinforce SEM results. Though the ANN has many types, the present study has employed one of the most common and renowned networks, i.e., the "multilayer perceptron" (MLP) (Zafar et al., 2021), to train the neural networks. ANNs usually include one input, more or one hidden layer, and one output layer, with no single rule for selecting the best values. The value of hidden layers is proportional to the problem's intricacy (Sheela & Deepa, 2013). The importance of predictors was assessed in two steps. First, we provide seven significant covariates as predicting variables (input layer), whereas GIA was applied as an output layer in the neural network. A sigmoid function was utilised to represent the activation function of neurons in both the hidden and output layers. Following prior researchers such as Zafar et al. (2021); Liébana-cabanillas et al. (2017), the ANN model was verified by employing the number of hidden nodes from 1 to 10. To minimise over-fitting, we employed ten-fold cross-validation, with 70% of the data employed to train the network model and 30% to test it.

The neural network prediction accuracy was estimated using the Root Mean Square Error (RMSE). The findings revealed that the average RMSE for GIA was 0.1337 for training data and 0.1323 for testing data. The disparity in produced values is minor, indicating that the model used provides high accuracy (Leong et al., 2018). Outcomes are given in Table 8. A sensitivity analysis was executed to gauge the importance and normalised importance of integrated covariates in the ANN model. The importance of incorporated constructs was computed by averaging their generated values in ten networks for predicting the output. Further, the normalised importance represents the ratio of each input variable to the highest, indicating that GFC was the most important predictor for GIA with a 0.223 importance value, followed by GPE, GHM, GSI, GEE, GIC, and GBI, i.e., 0.215, 0.208, 0.177, 0.162, 0.161, and 0.128 respectively (see Table 9). The graphical representation of the average and relative importance of each construct were shown in Fig. 2. Some minor differences were observed in the ranking of variables, but GFC and GPE ranking is comparable in both analyses. The non-linear and non-compensatory design of ANN models and their higher level of prediction accuracy may explain these differences.

Discussion and research implications

Discussion on key findings

This study incorporates the UTAUT to advance the conceptual framework for estimating the influence of specified decision-making factors on GIA – a previously relatively unexplored area. The empirical findings confirmed that GPE and GEE positively affect GBI accepting H1 and H2. These results support preceding studies of Ahn et al. (2016); Anser et al. (2020) by emphasising the insinuation of adopting sustainable and innovative technologies by UTAUT. The positive effects of these variables suggested that innovative green technology

Table 8
Validation of neural networks for training and testing data.

	Training Data				Testing Data			
Neural Networks	N	Sum of Square Error	Mean Square Error	RMSE	N	Sum of Square Error	Mean Square Error	RMSE
1	357	6.215	0.0174	0.1319	159	2.813	0.0177	0.1330
2	348	6.240	0.0179	0.1339	168	2.752	0.0164	0.1280
3	378	7.184	0.0190	0.1379	138	2.355	0.0171	0.1306
4	341	6.045	0.0177	0.1331	175	3.143	0.0180	0.1340
5	379	6.793	0.0179	0.1339	137	2.353	0.0172	0.1311
6	363	6.215	0.0171	0.1308	153	2.874	0.0188	0.1371
7	353	6.605	0.0187	0.1368	163	2.474	0.0152	0.1232
8	385	7.174	0.0186	0.1365	131	2.139	0.0163	0.1278
9	343	5.915	0.0172	0.1313	173	3.181	0.0184	0.1356
10	352	6.007	0.0170	0.1306	164	3.335	0.0203	0.1426
Average				0.1337				0.1323
St. Dev.				0.0026				0.0055

Table 9
Sensitivity analysis.

Neural Networks	GPE	GEE	GFC	GSI	GHM	GIC	GBI
1	0.234	0.650	0.231	0.096	0.134	0.167	0.073
2	0.590	0.111	0.189	0.205	0.130	0.210	0.095
3	0.133	0.169	0.073	0.192	0.148	0.090	0.195
4	0.245	0.118	0.311	0.126	0.132	0.028	0.049
5	0.099	0.094	0.244	0.194	0.065	0.190	0.114
6	0.146	0.110	0.306	0.051	0.101	0.225	0.067
7	0.153	0.105	0.231	0.105	0.122	0.169	0.114
8	0.217	0.121	0.182	0.037	0.470	0.208	0.189
9	0.150	0.111	0.198	0.203	0.750	0.157	0.107
10	0.180	0.032	0.263	0.560	0.026	0.169	0.274
Average Importance	0.215	0.162	0.223	0.177	0.208	0.161	0.128
Relative Importance	0.964	0.728	1.000	0.794	0.933	0.724	0.573
Normalized Importance	96.36	72.75	100.00	79.39	93.26	72.39	57.31

is easy to implement and enhances long-term performance in the current challenging business environment. Further, GHM and GSI positively impacted GBI, leading to our H3 and H4. Our results coincided with Ali et al. (2020); Wang et al. (2020). Prior researchers recommend that green thinking and social influence shape individuals' pleasure-seeking behaviour to purchase green products, ultimately conserving the environment. Ashfaq et al. (2021) also claim that social influence and hedonic motivation significantly influence intention to use the latest technology.

GFC most significantly affects GBI accepting H5, showing the outcome is congruent with Tariq et al. (2016). The results of their research accentuated that guidance and edification about innovative and green technology induce usage and GBI. Further, as internal stakeholders of the process, employees would only accept innovative technologies when they attained a particular level of technical support and assistance (Shahzad et al., 2020a). The GIC also positively affected GBI, accepting H6. Our results contradict Tam et al. (2020). The probable cause for this deviation is perhaps that consumers are now more environmentally conscious, prefer to use eco-friendly products, and are willing to pay higher values (Liu et al., 2021). Adopting innovative technology does not personify additional costs for consumers; on the contrary, it can offer financial and non-financial benefits.

Furthermore, the acceptance of H7 shows a substantial positive effect of GBI on GIA as predicted by UTAUT and is broadly coherent with the results of Venkatesh et al. (2012). Several studies suggested that behavioural intention can be used as a surrogate for actual technological adoption (Karampournioti & Wiedmann, 2022; Zafar et al., 2020). Thus, this study also predominantly evaluated the mediating effect of GBI as it instigates GIA. Our two-step mediation results show that GBI complementary partially mediates the integrated relationship towards GIA by accepting H8a to H8f. These results have also coincided with Ashfaq et al. (2021) and Ifedayo et al. (2021) in the broader context for technology adoption.

Lastly, this study also conducted MGA to evaluate the moderating role of organisational size among integrated relations towards GBI and GIA. The findings are distinctive and captivating as organisational size moderated structural relationships differently by accepting H9. Not every organisation can accept technological changes in production operations; it is a long process and requires immense investment/financial resources. Larger organisations can take advantage of economies of scale to adopt GI by increasing production levels. In a developing country like Pakistan, organisations do not have a specialised product line; they have diversified product lines. If they happen to own a specialised product line, their GIA levels might be higher. These results provide adequate evidence that GIA is a long-run effort that obliges an organisation to create considerable development in processes and products, inevitably invoking environmental risks. Finally, the ANN's overall findings support the relevance of integrated components. Sensitivity analysis revealed that GFC and GPE have relatively the highest importance towards GIA as predicted by SEM. Thus, we should consider the significance of these variables for achieving GIA outcomes.

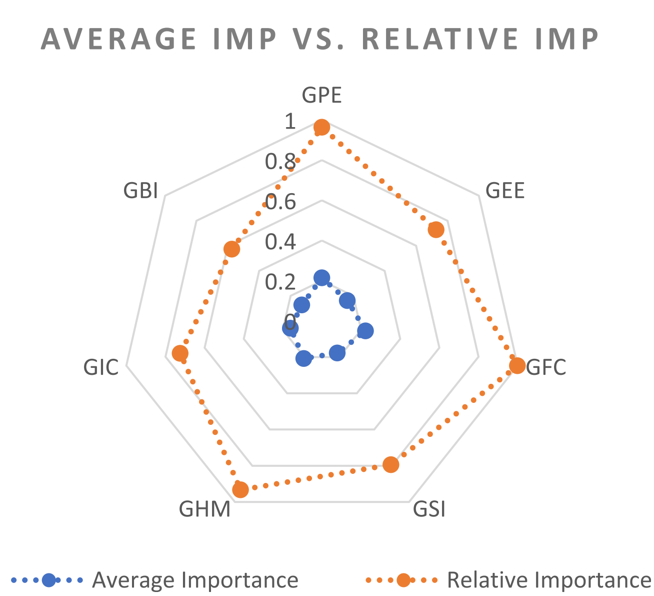

Fig. 2. Importance of each construct.

Theoretical implications

This research serves mainstream literature in a variety of areas. First, a technological adoption model based on UTAUT is validated, providing a new correlate to address the scarcity in the prior literature in the field of GI. We believe this is the first research exploring GIA through diverse decision-making factors with green attributes, i.e., GPE, GEE, GHM, GSI, GFC, GIC, GBI in a novel way through SEM and ANN in developing nations, i.e. Pakistan. Second, this study divulged the direct impact of GPE, GEE, GHM, GSI, GFC, and GIC on GBI and, further on, GIA – a novel phenomenon not operationalised in green and sustainable innovation literature previously. Besides, this study also underpinned the key mediating role of GBI and developed its complementary partial mediation, as behavioural intention reinforces actual technology adoption. The proliferation of ICT and digital manufacturing alters manufacturing processes and operations, significantly impacting GIA (Awan et al., 2020). Thus, our results demonstrate that the study of UTAUT for GIA is imperative in the current era of technology-based innovation.

Third, this research measured the moderating role of organisational size that facilitates the adoption levels of GI. The significant moderating results established that larger organisations promptly realised the importance of GI and effectively embraced SD agendas. This research evocatively contributes to the existing literature and offers a vital and comprehensive mechanism to promote green technology innovation. Finally, combining the two methodologies (i.e., PLS-SEM and ANN) yields new intuitions and emphasises the relevance of all independent variables contributing to GIA independently. The findings indicate that ANN appears to be a more capable predictive model, shown by the low RMSEs of all ANN models for testing and training datasets (Leong et al., 2018; Liébana-cabanillas et al., 2017).

Practical implications

This study has several practical contributions which facilitate managers and policymakers. First, the findings emphasised the relevance of diverse decision-making factors based on the UTAUT model to enhance GIA, which educates practitioners and enables organisations to achieve SD goals by promoting GI. Our work acknowledged that GIA is a helpful tool to persuade manufacturing organisations to consider and integrate innovative and cleaner production technologies into their operations to reduce the environmental burden while deciding their strategic initiatives (Awan et al., 2020). GIA stimulates organisations to offer a sustainable production and consumption model to concerned stakeholders.

Second, to reap the benefits of the SD plan 2030, developing economies such as Pakistan must undertake GI to compete with developed economies. By taking the example of China, they have achieved swift economic growth while undergoing severe resource exhaustion and ecological pollution (Zhu et al., 2010). There is growing pressure to invest in green technologies in these countries, and organisations are already burdened by emergency measures to stop environmental impact; one solution is adopting green technologies. For countries like Pakistan who are in developing mode, there is a possibility to learn from the practices of developed countries regarding environmental conservation. The government should promote and work effectively on a green business climate, i.e., "Punjab Green Development Program," to assist organisations in reducing their dependence on fossil fuels and maximising the use of renewable energy (World Bank, 2018). That will increase ecological awareness among industries and enhance economic growth. Besides, PPPs will also be helpful in providing the solution of advanced and green technologies at a lower cost.

Third, organisations should provide favourable working conditions and encourage employees to acquire more advanced knowledge for specialised business operations (including supply chain integration, innovation, and technology transfer) through education and training. Encountering software and hardware difficulties while using these innovative technologies can hinder the adoption of GI. Solving these difficulties is essential and needs top management and governmental support immediately. More investment should be allocated for the skill-building of employees regarding GIA, to help improve operational performance and profitability. Regular assistance can be offered through various means; technical consultants may offer ongoing product/service consultations to all stakeholders, and call centre services can provide prompt solutions to any problems.

Conclusion

The sustainable innovation debate is gaining momentum as numerous countries strive to achieve SD goals in the coming decade. This research has produced distinct outcomes that can be considered significant contributions to the mainstream literature. A comprehensive framework was presented in this research based on UTAUT model for influencing GIA in today's challenging business environments to improve SD. We used survey procedures to gather data from the manufacturing industries and employed SEM and ANN to validate our hypotheses and the relative importance of each variable. GIA made a substantial contribution by illuminating the significant relationships of GPE, GEE, GHM, GSI, GFC, and GIC to GBI and on GIA. Further, the illumination of the mediating role of GBI among these relations was also an imperative contribution. Besides, organisational size has a significant moderating effect on the ability to pursue GI differently among small, medium, and large organisations. The findings of ANN unveiled robustness by highlighting the relative importance of all consequential constructs towards GIA. These findings demonstrate deep insights to comprehend the role of critical green determinants that influence GIA, which aids organisations in succeeding in excellence and helping to achieve SD. Besides, the GI dream will never come true without adopting green practices and the latest innovative technologies.

This study suggests several areas to be researched in the future. Due to a lack of resources, it used a cross-sectional technique; a longitudinal approach could provide better and more accurate results. This study was limited to a particular sector; in the future, scholars should broaden its scope to include other industries and geographies to ensure generalizability. Some machine learning techniques can also be used to forecast more accurate and reliable outcomes. Finally, this paradigm may be tested by including cultural and political factors; however, the findings may vary in other regions.

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Appendix A: Summary of literature review

Authors	Methods and Theory	Objectives	Integrated Constructs
Han and Chen (2021)	800 Survey TRA	To uncover the antecedents of eco-innovation adoption by SMEs in Myanmar	Customer demands, Environmental concerns and regulations, Rivalry pressures, Eco-innovation adoption, and Firm innovation capabilities,
J. Lee et al. (2021)	432 Survey UTAUT	To discover the factors that affect behavioural intentions to purchase electronic vehicles	Effort Expectancy, Performance expectancy, Social influence, Facilitating conditions, Environmental concerns, and Behavioural intention
Ashfaq et al. (2021)	293 Survey BRT	To explore individual attitudes to Ant Forest mobile gaming and their continued usage intentions	Hedonic motivation, Social influence, Environmental benefits, Convenience, Attitude and User intention
Jun et al. (2021)	288 Survey and Conceptual Model	To highlight the core elements of green innovation adoption in SMEs in Pakistan	External partnership and cooperation, Government support, Market and customer factors, Rules and regulatory factors, Organisational and human resources, and Technological factors

(*continued*)

(*Continued*)

Authors	Methods and Theory	Objectives	Integrated Constructs
Anser et al. (2020)	Bibliometric Analysis TAM	To understand the key factors of the TAM model which enhances firms' green investment decision	Green supplier selection, Green industrial engineering, Green consumerism, Green procurement, Green innovation, Green product recovery, and Green purchase decisions
Zhao and Bacao (2020)	532 Survey UTAUT	To examine users' continuance intention of using food delivery apps	Effort expectancy, Performance expectancy, Social influence, Trust, Satisfaction, Confirmation, Perceived task-technology fit, and Continuance intention
Al-Saedi et al. (2020)	436 Survey and Meta-Analysis UTAUT	To observe the users' continuance intention to adopt and use M-payment technology	Perceived trust, Perceived risk, Self-efficacy, Perceived cost, Effort expectancy, Performance expectancy, Social influence, and Behavioural intention
Wu et al. (2019)	470 Survey TAM	To recognise the public adoption of electric vehicles	Green perceived usefulness, Perceived ease of use, Environmental concern, and Behavioural intention
Hsu et al., (2017)	320 Survey TAM and TPB	What factors influence the adoption of green information technology products for sustainable development	Perceived usefulness, Attitudes, Perceived behavioural control, Subjective norms, and Intention to purchase
Ma et al. (2017)	903 Surveys TAM	To explore consumers' perceptions about sustainable apparel products to determine purchase intentions	Perceived ease of use, Perceived usefulness, Attitude, and Behavioural intention to use
Ahn et al. (2016)	592 Survey UTAUT	To understand what factors drive the adoption of sustainable household technology	Performance expectancy, Compatibleness expectancy, Effort expectancy, Hedonic expectancy, Sustainable innovativeness, Social pressure, Environmentalism, and Behavioural intention
Huang and Kao (2015)	30 professionals UTAUT	To explore and predict the intentions to use, and use behaviours of Phablets	Social influence, Effort Expectancy, Performance expectancy, Facilitating conditions, Hedonic motivation, Price value, Habit, and Behavioural intention
Venkatesh et al. (2012)	1512 Survey UTAUT	To extend the scope of the Unified Theory of Acceptance and Use of Technology in the consumer context	Facilitating conditions, Performance expectancy, Effort Expectancy, Social influence, Hedonic motivation, Habit, Price value, and Behavioural intention

TRA=Theory of Reasoned Action, BRT=Behavioural Reasoning Theory, TAM=Technology Acceptance Model, UTAUT=Unified Theory of Acceptance and Use of Technology, TPB=Theory of Planned Behaviour

References

Ahmad, M., Khan, Z., Rahman, Z. U., Khattak, S. I., & Khan, Z. U. (2021). Can innovation shocks determine CO2 emissions (CO2e) in the OECD economies? A new perspective. *Economics of Innovation and New Technology*, *30*(1), 89–109. doi:10.1080/10438599.2019.1684643.

Ahn, M., Kang, J., & Hustvedt, G. (2016). A model of sustainable household technology acceptance. *International Journal of Consumer Studies*, *40*, 83–91. doi:10.1111/ijcs.12217.

Aibar-Guzmán, B., García-Sánchez, I. M., Aibar-Guzmán, C., & Hussain, N. (2022). Sustainable product innovation in agri-food industry: Do ownership structure and capital structure matter? *Journal of Innovation and Knowledge*, *7*,(1) 100160. doi:10.1016/j.jik.2021.100160.

Al-Saedi, K., Al-Emran, M., Ramayah, T., & Abusham, E. (2020). Developing a general extended UTAUT model for M-payment adoption. *Technology in Society*, *62*, 101293. doi:10.1016/j.techsoc.2020.101293.

Albino, V., Balice, A., & Dangelico, R. M. (2009). Environmental strategies and green product development: An overview on sustainability-driven companies. *Business Strategy and the Environment*, *18*(2), 83–96.

Ali, F., Ashfaq, M., Begum, S., & Ali, A. (2020). How "Green" thinking and altruism translate into purchasing intentions for electronics products: The intrinsic-extrinsic motivation mechanism. *Sustainable Production and Consumption*, *24*, 281–291. doi:10.1016/j.spc.2020.07.013.

Anser, M. K., Yousaf, Z., & Zaman, K. (2020). Green technology acceptance model and green logistics operations: "To see which way the wind is blowing. *Frontiers in Sustainability*, *1*(3), 1–9. doi:10.3389/frsus.2020.00003.

Ashfaq, M., Zhang, Q., Ali, F., Waheed, A., & Nawaz, S. (2021). You plant a virtual tree, we'll plant a real tree: Understanding users' adoption of the Ant Forest mobile gaming application from a behavioral reasoning theory perspective. *Journal of Cleaner Production*, *310*, 127394. doi:10.1016/j.jclepro.2021.127394.

Asiamah, N., Mensah, H. K., & Oteng-abayie, E. F. (2017). Do larger samples really lead to more precise estimates ? A simulation study. *American Journal of Educational Research*, *5*(1), 9–17. doi:10.12691/education-5-1-2.

Awan, U., Arnold, M. G., & Golgeci, I. (2020). Enhancing green product and process innovation : Towards an integrative framework of knowledge acquisition and environmental investment. *Business Strategy and the Environment*, 1–13. doi:10.1002/bse.2684.

Casey, T., & Wilson-Evered, E. (2012). Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT. *Computers in Human Behavior*, *28*(6), 2034–2045. doi:10.1016/j.chb.2012.05.022.

Chang, C. H., & Chen, Y. S. (2013). Green organisational identity and green innovation. *Management Decision*, *51*(5), 1056–1070. doi:10.1108/MD-09-2011-0314.

Chavoshi, A., & Hamidi, H. (2019). Social, individual, technological and pedagogical factors influencing mobile learning acceptance in higher education: A case from Iran. *Telematics and Informatics*, *38*(September 2018), 133–165. doi:10.1016/j.tele.2018.09.007.

Chen, Y.-S. (2008). The driver of green innovation and green image–green core competence. *Journal of Business Ethics*, *81*(3), 531–543.

Chen, Y. S., Lai, S. B., & Wen, C. T. (2006). The influence of green innovation performance on corporate advantage in Taiwan. *Journal of Business Ethics*, *67*(4), 331–339.

Choi, D., & Johnson, K. K. P. (2019). Influences of environmental and hedonic motivations on intention to purchase green products: An extension of the theory of planned behavior. *Sustainable Production and Consumption*, *18*, 145–155. doi:10.1016/j.spc.2019.02.001.

Chopdar, P. K., & Sivakumar, V. J. (2019). Understanding continuance usage of mobile shopping applications in India: The role of espoused cultural values and perceived risk. *Behaviour and Information Technology*, *38*(1), 42–64. doi:10.1080/0144929X.2018.1513563.

Cillo, V., Petruzzelli, A. M., Ardito, L., & Del Giudice, M. (2019). Understanding sustainable innovation: A systematic literature review. *Corporate Social Responsibility and Environmental Management*, *26*, 1012–1025.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates, Publishers. doi:10.1234/12345678.

Dangelico, R. M. (2017). What drives green product development and how do different antecedents affect market performance? A survey of Italian companies with eco-labels. *Business Strategy and the Environment*, *26*(8), 1144–1161. doi:10.1002/bse.1975.

Fernando, Y., Chiappetta Jabbour, C. J., & Wah, W. X. (2019). Pursuing green growth in technology firms through the connections between environmental innovation and sustainable business performance: Does service capability matter? *Resources, Conservation and Recycling*, *141*(2018), 8–20.

Forcadell, F.-J., Úbeda, F., & Aracil, E. (2021). Effects of environmental corporate social responsibility on innovativeness of Spanish industrial SMEs. *Technological Forecasting and Social Change*, *162*, 120355. doi:10.1016/j.techfore.2020.120355.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurements error. *Journal of Marketing Research*, *18*(4), 39–50.

Global Innovation Index. (2018). *Key findings report*. https://www.globalinnovationindex.org/about-gii#keyfindings

Guo, J., Cui, L., Sun, S. L., & Zou, B. (2022). How to innovate continuously? Conceptualising generative capability. *Journal of Innovation and Knowledge*, *7*,(2) 100177. doi:10.1016/j.jik.2022.100177.

Guo, R., Lv, S., Liao, T., Xi, F., Zhang, J., Zuo, X., Cao, X., Feng, Z., & Zhang, Y. (2020). Classifying green technologies for sustainable innovation and investment. *Resources, Conservation and Recycling*, *153*, 104580. doi:10.1016/j.resconrec.2019.104580.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). *Handbook of Market Research*. (2nd ed.). Sage. doi:10.1007/978-3-319-05542-8_15-1.

Han, M. S., & Chen, W. (2021). Determinants of eco-innovation adoption of small and medium enterprises : An empirical analysis in Myanmar. *Technological Forecasting & Social Change*, *173*, 121146. doi:10.1016/j.techfore.2021.121146.

Hansen, M. H., Li, H., & Rune, S. (2018). Ecological civilisation: Interpreting the Chinese past, projecting the global future. *Global Environmental Change*, *53*, 195–203. doi:10.1016/j.gloenvcha.2018.09.014.

Harman, H. H. (1976). *Modern Factor Analysis* (3rd ed.). University of Chicago Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8.

Hilkenmeier, F., Fechtelpeter, C., & Decius, J. (2021). How to foster innovation in SMEs : Evidence of the effectiveness of a project-based technology transfer approach. *The Journal of Technology Transfer*, 1–29.

Hsu, C. L., Chen, M. C., & Lin, Y. H. (2017). Information technology adoption for sustainable development: Green e-books as an example. *Information Technology for Development*, *23*(2), 261–280. doi:10.1080/02681102.2017.1298078.

Huang, C. Y., & Kao, Y. S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. *Mathematical Problems in Engineering*, *603747*. doi:10.1155/2015/603747.

Ifedayo, A. E., Ziden, A. A., & Ismail, A. B. (2021). Mediating effect of behavioural intention on podcast acceptance. *Education and Information Technologies*, *26*(3), 2767–2794. doi:10.1007/s10639-020-10385-z.

Jahanshahi, A. A., Al-Gamrh, B., & Gharleghi, B. (2020). Sustainable development in Iran post-sanction: Embracing green innovation by small and medium-sized enterprises. *Sustainable Development*, *28*(4), 781–790. doi:10.1002/sd.2028.

Jansson, J. (2011). Consumer eco-innovation adoption: Assessing attitudinal factors and perceived product characteristics. *Business Strategy and the Environment*, *20* (3), 192–210. doi:10.1002/bse.690.

Jun, W., Ali, W., Bhutto, M. Y., Hussain, H., & Khan, N. A. (2021). Examining the determinants of green innovation adoption in SMEs : A PLS-SEM approach. *European Journal of Innovation Management*, *24*(1), 67–87. doi:10.1108/EJIM-05-2019-0113.

Karampournioti, E., & Wiedmann, K. P. (2022). Storytelling in online shops: the impacts on explicit and implicit user experience, brand perceptions and behavioral intention. *Internet Research*, *32*(7), 228–259. doi:10.1108/INTR-09-2019-0377.

Khan, S. J., Dhir, A., Parida, V., & Papa, A. (2021). Past, present, and future of green product innovation. *Business Strategy and the Environment*, 1–26. doi:10.1002/bse.2858.

Klein, S. P., Spieth, P., & Heidenreich, S. (2021). Facilitating business model innovation: The influence of sustainability and the mediating role of strategic orientations. *Journal of Product Innovation Management*, 271–288. doi:10.1111/jpim.12563.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, *11*(4), 1–10. doi:10.4018/ijec.2015100101.

Lee, J., Baig, F., Talpur, M. A. H., & Shaikh, S. (2021). Public intentions to purchase electric vehicles in Pakistan. *Sustainability*, *13*(10), 1–18. doi:10.3390/su13105523.

Lee, K., Shim, E., Kim, J., & Nam, H. (2021). The influence of product innovation messages on the intention to purchase incumbent products. *Journal of Innovation and Knowledge*, *6*(3), 154–166. doi:10.1016/j.jik.2021.01.003.

Leong, L. Y., Jaafar, N. I., & Ainin, S. (2018). The effects of Facebook browsing and usage intensity on impulse purchase in f-commerce. *Computers in Human Behavior*, *78*, 160–173. doi:10.1016/j.chb.2017.09.033.

Li, L., Msaad, H., Sun, H., Tan, M. X., Lu, Y., & Lau, A. K. W. (2020). Green innovation and business sustainability: New evidence from energy intensive industry in China. *International Journal of Environmental Research and Public Health*, *17*(21), 1–18. doi:10.3390/ijerph17217826.

Liébana-cabanillas, F., Marinkovic, V., De Luna, I. R., & Kalinic, Z. (2017). Predicting the determinants of mobile payment acceptance : A hybrid SEM-neural network approach. *Technological Forecasting & Social Change*1. doi:10.1016/j.techfore.2017.12.015 October.

Lin, C.-Y., & Ho, Y.-H. (2008). An empirical study on logistics service providers' intention to adopt green innovations. *Journal of Technology Management & Innovation*, *3*(1), 17–26.

Lin, C. Y., Alam, S. S., Ho, Y. H., Al-Shaikh, M. E., & Sultan, P. (2020). Adoption of green supply chain management among SMEs in Malaysia. *Sustainability*, *12*(16), 1–15. doi:10.3390/su12166454.

Liu, L., Wang, Z., & Zhang, Z. (2021). Matching-game approach for green technology investment strategies in a supply chain under environmental regulations. *Sustainable Production and Consumption*, *28*, 371–390. doi:10.1016/j.spc.2021.06.001.

Ma, Y., Hou, G., Yin, Q., Xin, B., & Pan, Y. (2018). The sources of green management innovation : Does internal efficiency demand pull or external knowledge supply push? *Journal of Cleaner Production*, *202*, 582–590. doi:10.1016/j.jclepro.2018.08.173.

Ma, Y. J., Gam, H. J., & Banning, J. (2017). Perceived ease of use and usefulness of sustainability labels on apparel products: Application of the technology acceptance model. *Fashion and Textiles*. doi:10.1186/s40691-017-0093-1.

Maasoumi, E., Heshmati, A., & Lee, I. (2020). Green innovations and patenting renewable energy technologies. *Empirical Economics*. doi:10.1007/s00181-020-01986-1.

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modelling, Helping researchers discuss more sophisticated models. *Industrial Management and Data Systems*, *116*(9), 1849–1864.

Nysveen, H., & Pedersen, P. E. (2016). Consumer adoption of RFID-enabled services. Applying an extended UTAUT model. *Information Systems Frontiers*. doi:10.1007/s10796-014-9531-4.

Prajapati, B., Dunne, M., & Armstrong, R. (2010). Sample size estimation and statistical power analyses. *Optometry Today*.

Shahzad, M., Qu, Y., Rehman, S. U., Ding, X., & Razzaq, A. (2022). Impact of stakeholders' pressure on green management practices of manufacturing organizations under the mediation of organizational motives. *Journal of Environmental Planning and Management*, 1–24. doi:10.1080/09640568.2022.2062567.

Shahzad, M., Qu, Y., Zafar, A. U., & Appolloni, A. (2021). Does the interaction between the knowledge management process and sustainable development practices boost corporate green innovation? *Business Strategy and the Environment*, 1–17. doi:10.1002/bse.2865.

Shahzad, M., Qu, Y., Zafar, A. U., Ding, X., & Rehman, S. U. (2020a). Translating stakeholders' pressure into environmental practices - The mediating role of knowledge management. *Journal of Cleaner Production*, *275*, 124163.

Shahzad, M., Qu, Y., Zafar, A. U., Rehman, S. U., & Islam, T. (2020b). Exploring the influence of knowledge management process on corporate sustainable performance through green innovation. *Journal of Knowledge Management*, *24*(9), 2079–2106.

Shang, D., & Wu, W. (2017). Understanding mobile shopping consumers' continuance intention. *Industrial Management and Data Systems*, *117*(1), 213–227. doi:10.1108/IMDS-02-2016-0052.

Sheela, K. G., & Deepa, S. N. (2013). Review on methods to fix number of hidden neurons in neural networks. *Mathematical Problems in Engineering*, *2013*, 1–11.

Shin, J., Kim, Y. J., Jung, S., & Kim, C. (2022). Product and service innovation: Comparison between performance and efficiency. *Journal of Innovation and Knowledge*, *7*, 100191. doi:10.1016/j.jik.2022.100191.

Shu, C., Zhou, K. Z., & Xiao, Y. (2016). How green management influences product innovation in China : The role of institutional benefits. *Journal of Business Ethics*, *133*, 471–485. doi:10.1007/s10551-014-2401-7.

Sim, J. J., Tan, G. W. H., Wong, J. C. J., Ooi, K. B., & Hew, T. S. (2014). Understanding and predicting the motivators of mobile music acceptance - A multi-stage MRA-artificial neural network approach. *Telematics and Informatics*, *31*(4), 569–584.

Skare, M., & Riberio Soriano, D. (2021). How globalisation is changing digital technology adoption: An international perspective. *Journal of Innovation and Knowledge*, *6* (4), 222–233. doi:10.1016/j.jik.2021.04.001.

Song, Malin, Saen, R. F., Fisher, R., & Tseng, M (2019). Technology innovation for green growth and sustainable resource management. *Resources, Conservation and Recycling*, *141*(October 2018), 501. doi:10.1016/j.resconrec.2018.05.003.

Song, Moxi, Yang, M. X., Zeng, K. J., & Feng, W (2020). Green knowledge sharing, stakeholder pressure, Absorptive capacity, and green innovation: Evidence from Chinese manufacturing firms. *Business Strategy and the Environment*, *29*(3), 1517–1531. doi:10.1002/bse.2450.

Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research*, *79*(2), 625–649. doi:10.3102/0034654308325896.

Tam, C., Santos, D., & Oliveira, T. (2020). Exploring the influential factors of continuance intention to use mobile Apps: Extending the expectation confirmation model. *Information Systems Frontiers*, *22*(1), 243–257. doi:10.1007/s10796-018-9864-5.

Tariq, S., Jan, F. A., & Ahmad, M. S. (2016). Green employee empowerment: a systematic literature review on state-of-art in green human resource management. *Quality and Quantity*. doi:10.1007/s11135-014-0146-0.

Tseng, M. L., Chiu, A. S. F., & Liang, D. (2018). Sustainable consumption and production in business decision-making models. *Resources, Conservation and Recycling*, *128*, 118–121. doi:10.1016/j.resconrec.2017.02.014.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178.

Wang, X., Goh, D. H. L., & Lim, E. P. (2020). Understanding continuance intention toward crowdsourcing games: A longitudinal investigation. *International Journal of Human-Computer Interaction*, *36*(12), 1168–1177. doi:10.1080/10447318.2020.1724010.

Wei, S., Ang, T., & Jancenelle, V. E. (2018). Willingness to pay more for green products: The interplay of consumer characteristics and customer participation. *Journal of Retailing and Consumer Services*, *45*(September), 230–238. doi:10.1016/j.jretconser.2018.08.015.

Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly*, *33*(1), 177.

Wong, S. K. S. (2013). Environmental requirements, knowledge sharing and green innovation: Empirical evidence from the electronics industry in China. *Business Strategy and the Environment*, *22*(5), 321–338. doi:10.1002/bse.1746.

World Bank. (2018). World Bank Project : *Punjab green development* program. https://projects.worldbank.org/en/projects-operations/project-detail/P165388?lang%2525C2%2525BCen=

Wu, J., Liao, H., Wang, J. W., & Chen, T. (2019). The role of environmental concern in the public acceptance of autonomous electric vehicles: A survey from China. *Transportation Research Part F*, *60*, 37–46. doi:10.1016/j.trf.2018.09.029.

Xie, X., Hoang, T. T., & Zhu, Q. (2022). Green process innovation and financial performance: The role of green social capital and customers' tacit green needs. *Journal of Innovation and Knowledge*, *7*,(1) 100165. doi:10.1016/j.jik.2022.100165.

Yang, T., Long, R., Wenbo, L., & Rehman, S. U. (2016). Innovative application of the public – Private partnership model to the electric vehicle charging infrastructure in China. *Sustainability (Switzerland)*, *8*(738), 1–18. doi:10.3390/su8080738.

Zafar, A. U., Qiu, J., & Shahzad, M. (2020). Do digital celebrities' relationships and social climate matter? Impulse buying in f-commerce. *Internet Research*. doi:10.1108/INTR-04-2019-0142.

Zafar, A. U., Shen, J., Shahzad, M., & Islam, T. (2021). Relation of impulsive urges and sustainable purchase decisions in the personalised environment of social media. *Sustainable Production and Consumption*, *25*, 591–603. doi:10.1016/j.spc.2020.11.020.

Zailani, S., Govindan, K., Iranmanesh, M., Shaharudin, M. R., & Sia Chong, Y. (2015). Green innovation adoption in automotive supply chain: The Malaysian case. *Journal of Cleaner Production*. doi:10.1016/j.jclepro.2015.06.039.

Zhao, Y., & Bacao, F. (2020). What factors determining customer continuingly using food delivery apps during 2019 novel coronavirus pandemic period? *International Journal of Hospitality Management*, *91*, 102683. doi:10.1016/j.ijhm.2020.102683.

Zhu, Q., Geng, Y., & Lai, K.hung. (2010). Circular economy practices among Chinese manufacturers varying in environmental-oriented supply chain cooperation and the performance implications. *Journal of Environmental Management*. doi:10.1016/j.jenvman.2010.02.013.