Generative AI Literacy and Social Innovation Intention Among University Students: The Dual Mediating Roles of Social Opportunity Recognition and Social Entrepreneurial Self-Efficacy

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Abstract
The growing global grand challenges and the prevalence of socioeconomic disparities have increased the demand for business practices that create economic and social value at the same time. Although Generative Artificial Intelligence (GenAI) is being widely used, no studies have been conducted to assess how GenAI capabilities lead to social innovation intentions through cognitive and motivation process. Based on the Social Cognitive Theory and the Information Processing Theory, the current study constructs and tests a dual mediation model explaining how Generative AI Literacy (GAIL) impacts Social Innovation Intention (SII) through Social Opportunity Recognition (SOR) and Social Entrepreneurial Self-Efficacy (SESE). The quantitative cross-sectional study involved a sample of 550 university students and participants in incubators of technology entrepreneurs and innovations from educational institutions and incubators in India. The covariance-based structural equation model (CB-SEM) was analyzed in IBM SPSS AMOS version 28, with the calculation of indirect effects done using bias-corrected bootstrapping based on 5,000 resamples. Results indicate that GAIL has a significant impact on SII ($\beta = 0.185$, $p < 0.001$). Indirect paths found to be significant includes SOR with a 0.128 effect (CI at 95% is [0.085, 0.180]) and a stronger effect through SESE at 0.188 (CI at 95% is [0.139, 0.245]). The significant direct relation along with both indirect routes confirm complementary parallel mediation. The results put GenAI Literacy as a technology usability notion using different cognitive and agentive means for support of Social Innovation intention. The research is contributing to the field of digital entrepreneurship and providing useful insights for universities, policymakers, and incubators to create responsible GenAI-supported entrepreneurial learning and social innovation systems.

Keywords: Generative AI Literacy, Social Innovation Intention, Social Opportunity Recognition, Social Entrepreneurial Self-Efficacy, Social Cognitive Theory, Information Processing Theory, Digital Social Entrepreneurship

Introduction

The demand for effective market-driven solutions that can create positive economic and social impact has increased due to global issues such as environmental degradation and rapidly rising social inequality (Mair & Martí, 2006; Saebi et al., 2019). The notion of social entrepreneurship arises as a much-needed tool to solve complex social problems in situations when traditional market and state mechanisms fail to produce the necessary outcome (Austin & Seitanidi, 2012; George et al., 2021). Thus, it is crucial to study psychological, cognitive, and technological factors that shape people's social innovation and entrepreneurship intentions (Hockerts, 2017). Despite being one of the hot topics of interest for scholars, research on social entrepreneurship intentions is mainly based on the existing theories of intention such as the Theory of Planned Behavior (Ajzen, 1991) and the Entrepreneurial Event Model (Shapero & Sokol, 1982). While these theories are useful, they do not explain how innovations in technology can affect people's thinking and possibilities when dealing with complex social challenges. Social venture creation is a process embedded in vibrant contexts featuring information asymmetry, institutional voids, and conflicting stakeholder interests (Mair & Martí, 2006). This means that social innovators, in order to deal with ambiguities, must possess something more than a good attitude; they must be able to receive the necessary information, identify the emerging opportunities, and find possible solutions to complex social issues. Changes brought by

Generative Artificial Intelligence (GenAI) and analytical tools make the ways people acquire, process, and use information in innovation and decision-making different (Banh & Strobel, 2023; Dwivedi et al., 2021). Therefore, Generative AI Literacy, which refers to skills and abilities needed to comprehend, use, critique, and apply Generative AI technologies, is becoming an important competency in modern decision-making contexts (Ng et al., 2024). However, entrepreneurship literature lacks the theory regarding the relationship between GenAI literacy and the agent of human being, which affects social opportunity recognition and intention for social innovation.

This research takes into account two theoretical approaches to fill this gap: Social Cognitive Theory developed by Bandura, 1986, 2001 and Information Processing Theory introduced by Simon (1962) and Galbraith (1974). According to the Social Cognitive Theory, human behavior is demonstrated through the interaction of cognitive, environmental, and behavioral elements (Bandura, 1986). The most important idea of this theory is the belief of individuals in their own capabilities that help them do something (Bandura, 1997). At the same time, the Information Processing Theory describes the process of acquiring, absorbing, and systemizing information by an individual in decision-making processes (Simon, 1962; Bettman, 1979). Based on these two theories, Generative AI Literacy is defined in the present research as a socio-technical capability that can enable people interpret and process complex pieces of information that helps them recognize social opportunities and develop their social entrepreneurial self-efficacy. It can be assumed that cognitive and motivational mechanisms mentioned above would ultimately provide individuals with higher intentions in social innovation sphere.

In order to further understand the process of social innovation, this research suggests and tests a dual-mediation model which includes Social Opportunity Recognition and Social Entrepreneurial Self-Efficacy as two separate but interrelated mechanisms that link Generative AI Literacy to the intention of social innovation. The first construct, Social Opportunity Recognition, enables the use of GenAI for identifying and understanding social customer needs which can be considered as the cognitive mechanism while the second one, Social Entrepreneurial Self-Efficacy, represents the agency mechanism which allows individuals to feel capable of doing socially-oriented entrepreneurship. This study discusses the mediating role of both concepts together so that it can provide a more thorough explanation of how certain technological competencies can be translated into the intentions of doing entrepreneurship for social betterment instead of examining it as a simple correlation between technological literacy and social innovation intentions. The present study contributes in three ways to the literature on social entrepreneurship and digital innovation. First, it broadens intention-based approaches by positioning Generative AI Literacy as an emerging cognitive-technological antecedent in Social Opportunity Recognition, Social Entrepreneurial Self-Efficacy, and Social Innovation Intention. Second, it sheds light on the way General AI Literacy transforms into socially oriented entrepreneurial intentionality through the concept of dual mediation, whereby Social Opportunity Recognition serves as the cognitive mechanism and Social Entrepreneurial Self-Efficacy acts as an agentic mechanism. Finally, it provides practical suggestions for educational institutions and policymakers involved in the design of educational and entrepreneurial development programs that aim to develop the entrepreneurial potential of future social innovators.

2. Theoretical Background and Hypotheses Development:

2.1 Social Cognitive Theory and Information Processing Lens

This particular research employs a theoretical framework known as the integration of Social Cognitive Theory (Bandura, 1986, 2001) and Information Processing Theory (Simon, 1962; Galbraith, 1974) to reveal the process of Generative AI Literacy turning into social innovation intention on the basis of cognitive and agentic mechanisms. The Social Cognitive Theory states that the functioning of humans comes from the process called triadic reciprocal causation where cognitive factors of the individual, behavior, and environmental influences are interacting with one another (Bandura, 1986). Self-efficacy is the fundamental concept of this agentic theory that refers to the person's belief in their skills to perform actions necessary to cope with particular situations (Bandura, 1997). Hence, Social Cognitive Theory can be regarded as a suitable theory to describe how perceived competence shapes motivation and the intention.

Nevertheless, it’s important to note that studying the phenomenon of social innovation intentions necessitates investigating how individuals process their environment's complicated and uncertain information. The Information Processing Theory is used to examine the way in which people acquire and process, classify, and use information under complicated and uncertain circumstances when making decisions (Simon, 1962; Bettman, 1979; Galbraith, 1974). In the context of social ventures, the environmental information could be characterized by fragmentation, ambiguity, and multiplicity (Mair & Martí, 2006). The integration of these theories suggests that cognitive processing and the personal agency play different roles: while the Information Processing Theory shows how information is interpreted, the Social Cognitive Theory is about how the perceived ability and

efficacy results in actions. It is worth noting that Generative AI Literacy is considered an emerging socio-technical competence that enables one to deal better with complicated information and also makes one feel capable to perform ventures that are aimed at social good. These waves of thinking build the theoretical ground for the discussion of how Generative AI Literacy might contribute to social innovation intentions through opportunity recognition and social entrepreneurial self-efficacy.

2.2 Generative AI Literacy and Social Innovation Intention

Social innovation intent is the individual's objective to create innovative responses to social issues (Hockerts, 2017). The process of managing the creation of a social innovation requires one to deal with poorly defined social problems, obtain knowledge from different fields, and create adequate solutions to complicated social issues (Saebi et al., 2019). Generative AI Literacy might help people with the much-needed cognitive abilities which would help them in reaching the social innovation creation objectives (Ng et al., 2024). The higher the Generative AI Literacy the better an individual would be able to achieve generation and implementation of GenAI (Banh & Strobel, 2023). Generative AI Literacy may mitigate some of the information and cognitive difficulties experienced during the process of generating answers to complicated social issues by facilitating these cognitive tasks (Dwivedi et al., 2021). People are more likely to commit to social innovation when they believe they can use GenAI effectively to examine and improve solutions. Therefore, we hypothesize that Generative AI literacy positively affects the intention to cultivate social innovations.

Hence, we propose:

H_1: Generative AI Literacy is positively related to Social Innovation Intention.

2.3 Generative AI Literacy and Social Opportunity Recognition

Social opportunity recognition is the cognitive process that allows individuals to detect social needs that have yet to be satisfied, social problems, and opportunities for generating social value and interpret them as some opportunities that can be acted upon (Corner & Ho, 2010). In contrast to general opportunity recognition, social opportunity recognition implies facing complicated social realities, several interests of stakeholders, and consequences of solutions to be developed (Bacq & Alt, 2018). From the Information Processing perspective, opportunity recognition depends on how information is received, interpreted, organized, and linked and the cognitive schemes through which the signals from the environment are evaluated (Baron, 2006). Generative AI Literacy has the potential to enhance such information-processing processes of individuals, thus making them able to engage with, integrate and assess different types of information more efficiently (Ng et al., 2024). People who are skilled in using generative AI are apparently in a better position to access public information, study policy papers, understand local opinions and other forms of public information to discover existing needs and ways to meet them (Banh & Strobel, 2023). Hence, rather than just increasing the amount of information people have, using GenAI efficiently enables people to make disparate information more coherent as it relates to social challenges and potential solutions. This improved ability to comprehend information opens the door to identifying meaningful social opportunities.

That is why, we propose a hypothesis:

H_2: Generative AI Literacy is positively related to Social Opportunity Recognition.

2.4 Social Opportunity Recognition and Social Innovation Intention

The identification of a feasible social opportunity acts as a crucial connection linking the knowledge of societal issues with the commitment to pursue innovative solutions (Hockerts, 2017). When individuals come across a defined opportunity to deal with the social problem, they are in a better position to evaluate possible solutions and resources needed to bring about social change (Corner & Ho, 2010; Saebi et al., 2019). Accordingly, social opportunity identification provides a basis for converting wider awareness of social issues into more distinct intentions. In addition, the identification of a social opportunity might decrease the uncertainty related to the possible ways of acting by creating a clearer picture of the problem to deal with and the value that can be generated (Bacq & Alt, 2018). Greater clarity can make the initiative more feasible and desirable. People who are better able to identify the opportunities for satisfying social needs will be more likely to commit to a social innovation project.

Therefore, we propose:

H_3: Social Opportunity Recognition is positively related to Social Innovation Intention.

2.5 Generative AI Literacy and Social Entrepreneurial Self-Efficacy

Social Entrepreneurial Self-Efficacy is the term that describes a person's belief in their ability to carry out the activities needed to launch and run a socially minded startup like recognizing possibilities, using resources, resolving social issues, and balancing different stakeholders' interests (Hockerts, 2017). Bandura (1997) claims that the development of self-efficacy occurs due to components such as experiences of succeeding in doing something, learning from others' experiences, receiving encouragement from others, and interpreting one's physical and emotional state. Generative AI literacy might shape such perceptions about one's capability since it allows people to make use of GenAI technologies in order to tackle complicated cognitive and entrepreneurial processes. Those who have higher levels of gen AI literacy would be able to

ideate and evaluate ideas, formulate business proposals, test various methods, and acquire decision-making information (Ng et al., 2024; Banh&Strobel, 2023; Dwivedi et al., 2021). Because of this, cognitive assistance can take place, which will help to perceive the manageability of complicated entrepreneurial missions. As people become better able to use GenAI to tackle problems and perform activities related to their business, they will surely strengthen their trust in their capabilities in the domain.

Hence, we propose:

H_4: Generative AI Literacy is positively related to Social Entrepreneurial Self-Efficacy.

2.6 Social Entrepreneurial Self-Efficacy and Social Innovation Intention

The Social Cognitive Theory considers self-efficacy as the primary factor in the motivation, objectives and intentions of individuals (Bandura, 1986, 2001). Individuals would initiate and continue activities if they believe they have the necessary abilities enabling them to execute them properly. On the contrary, an individual's perception of inability prevents him from participating in the activities that include difficulties (Bandura, 1997). The significance of this mechanism of self-efficacy is particularly noticeable in the case of social innovations where socially oriented entrepreneurship requires risk-taking, involvement of other parties to be successful and other contentious issues (Mair & Martí, 2006). Research has shown that those with higher Social Entrepreneurial Self-Efficacy are more inclined to believe that socially innovative endeavors are possible for them and that they possess the appropriate skills to tackle the issues involved in the creation and introduction of social solutions (Hockerts, 2017). Thus, one can conclude that positive beliefs concerning one's capabilities can increase the level of motivation and the desire to commit to social entrepreneurship. Hence, it is plausible to presume that Social Entrepreneurial Self-Efficacy is positively related to Social Innovation Intention.

Therefore, we propose:

H_5: Social Entrepreneurial Self-Efficacy is positively related to Social Innovation Intention.

2.7 Mediating Roles of Social Opportunity Recognition and Social Entrepreneurial Self-Efficacy

By combining Information Processing Theory and Social Cognitive Theory, we can understand the link between Generative AI Literacy and Social Innovation Intention in terms of two processes. Generative AI Literacy is an important element of technology, but it does not necessarily culminate in the intention to engage in social innovation. In fact, the influence of technology could depend on cognitive and agentic processes of people that allow them to analyze information and form the appropriate mindset.

The primary process is one of cognitive recognition. Generative AI Literacy helps people think critically so that they can find unfulfilled societal demands and chances to create social value. As soon as people notice a potential social opportunity, they will set clear goals and take innovative actions. Accordingly, Social Opportunity Recognition is projected to be one of the mediators of the relationship between Generative AI Literacy and Social Innovation Intention. The next model concerns agentive recognition. Generative AI Literacy illustrates how one can succeed in complex cognitive and entrepreneurial practices, giving rise to competence perception. The higher one's Social Entrepreneurial Self-Efficacy is, the more confident one becomes about the capability to conduct social entrepreneurship. So, Social Entrepreneurial Self-Efficacy may be one of the mediators for the relationship between Generative AI Literacy and Social Innovation Intention. But taken together these processes indicate that Generative AI Literacy may affect the social innovation intention in terms of both what individuals can identify and what they think they can do. Therefore, analyzing these mechanisms at the same time brings a more integrated understanding of how the new technological capability can be transformed into social entrepreneurial intentions.

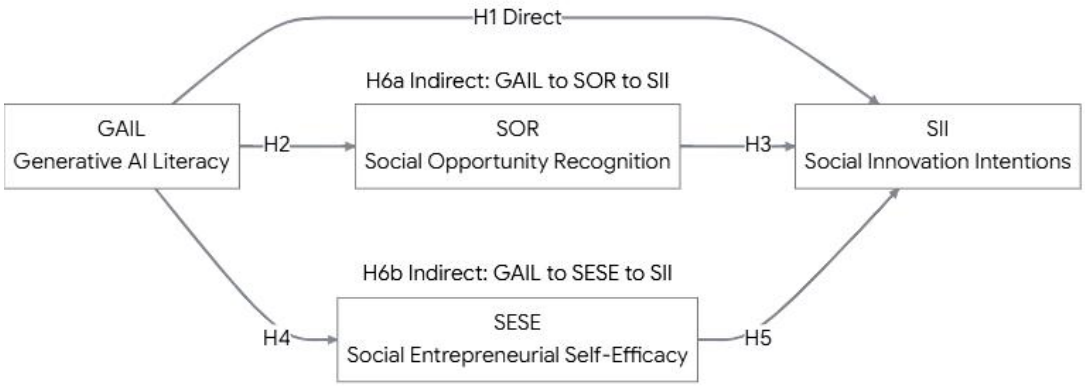
Therefore, we hypothesize:

H6a: Social Opportunity Recognition mediates the relationship between Generative AI Literacy and Social Innovation Intention.

H6b: Social Entrepreneurial Self-Efficacy mediates the relationship between Generative AI Literacy and Social Innovation Intention.

The complete conceptual framework and hypothesized relationships are presented in Figure 1.

Figure 1: Conceptual Framework



3. Methodology:

3.1 Research Design and Sampling Procedure

The research used a quantitative, cross-sectional survey research design to empirically investigate the proposed dual mediation model that connects Generative AI Literacy (GAIL) to Social Innovation Intention (SII) via Social Opportunity Recognition (SOR) and Social Entrepreneurial Self-Efficacy (SESE). The study population included undergraduate and postgraduate students in commerce, technology, and entrepreneurship, in addition to the incubatees who are connected with university-supported technology business incubators. India serves as a suitable empirical setting for the present study as it has a rapid digital market, a large youth population, and a growing focus on technology-based innovations and social entrepreneurship.

The collection of data was accomplished through an organized self-administered e-questionnaire in a time span of 4 months from December 2025 up to March 2026. Individuals had the options to participate voluntarily in the study in return the participants were promised of being anonymous and maintaining the confidentiality of their participation (Podsakoff et al., 2003). Eight hundred and twenty requests were sent across by different means of electronic communication including mailing lists and university incubator networks. Out of the 612 questionnaires filled, questions were scanned to ensure they are complete, respondents' replies are acceptable and multivariate outliers arising from the responses. The incomplete filled questionnaires and multivariate outliers from the respondents were filtered through the screening process. Upon completion of the screening stage, five hundred and fifty of the responses were received. The final sample size of 550 proved to be sufficient for the execution of covariance-based Structural Equation Modeling (CB-SEM) applying the Maximum Likelihood estimation process in IBM SPSS AMOS. The appropriateness of the sample was supported by a relatively high count of valid cases in respect of four measurements (Kline, 2016; Hair et al., 2019). Initial analysis of univariate normality showed that skewness values varied from -0.58 to +0.42 while kurtosis values were in the -0.49 and +0.65 range, thus demonstrating no significant violation from the conditions of maximum likelihood estimation (Kline, 2016).

3.2 Construct Operationalization and Measurement Scales

The exploration appears to have analyzed four different latent constructs, namely; generative AI literacy, social opportunity identification, social entrepreneurial self-efficacy, and social innovation intention. The operationalization of all the constructs was carried out through a multi-item measurement scale derived from the existing literature but refined to fit the notion of generative AI and social entrepreneurship. The responses to all the measurement items were captured using a 5-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Before starting the data collection, a pilot study was conducted with 40 seniors in business and technology to improve the clarity, readability, and face validity of the proposed tool. Thus, a few minor changes were made to the language of the questionnaire to make the measurement items easier to understand, without altering their ideational meaning.

Generative AI Literacy (GAIL): Generative AI Literacy consists of four items that identify how well respondents can familiarize themselves with generative AI technologies. The elements of this construct correspond with the extent of knowledge of generative AI and its capabilities (GAIL1), the propensity to generate effective prompts and critically assess AI outputs (GAIL2), awareness of ethical matters including algorithmic discrimination and social implications of AI usage (GAIL3), and the ability to apply generative AI in solving problems (GAIL4). The items were adapted from relevant literature in generative AI and AI literacy (Ng et al., 2021; Kong et al., 2023).

Social Opportunity Recognition (SOR): Social Opportunity Recognition refers to the process by which people Identify unfulfilled social needs and recognize opportunities to create social value. Following the Information Processing approach used in this study, Social Opportunity Recognition captures the processes through which individuals identify untapped social or environmental problems (SOR1), associate social problems with technological solutions (SOR2), evaluate opportunities for viability (SOR3), and discern opportunities for

creating sustainable social value (SOR4). The measures used here were borrowed from literature on opportunity recognition and social entrepreneurship (Corner & Ho, 2010; Kraus et al., 2017).

Social Entrepreneurial Self-Efficacy (SESE): SESE is the agentic pathway of our model and refers to individuals' perception of their ability to perform activities related to socially oriented entrepreneur activities. The sophistication is assessed through four items giving insight into the confidence of individuals in starting and managing a social endeavor (SESE1), finding necessary resources and support (SESE2), managing risks and uncertainties arising from the entrepreneurial activity (SESE3), and employing the existing technologies for supporting and scaling social impact (SESE4). The items were modified from the previous studies on the concepts of entrepreneurial self-efficacy and social entrepreneurial self-efficacy (Zhao et al., 2005; Hockerts, 2017).

Social Innovation Intention (SII): The concept of social innovation intention is translated into a dependent construct illustrating a person's desire and enticement to develop innovative solutions to solve problems existing in society. Four items were utilized to indicate the respondents' intention to create or participate in a social initiative (SII1), develop different plans for local sustainability challenges (SII2), find a job that has a measurable social impact (SII3), and conduct various projects aimed at achieving social goals, including those defined by the SDGs (SII4). The items used in the measurements were taken from the works on entrepreneurship intention and social entrepreneurship (Krueger et al., 2000; Thompson, 2009).

3.3 Common Method Bias Diagnostics

Since predictor, mediator, and outcome were measured from same respondents through cross-sectional self-report questionnaire, alternative strategies were applied to tackle the issues related to Common Method Bias (CMB) (Podsakoff et al., 2003). As for procedures, issues concerning anonymity and confidentiality were mentioned to respondents, the questions concerning constructs' definitions were not disclosed to respondents' knowledge that it may bias their responses, and the order of items was chosen in a way that diminishes chances of the respondents' linking predictors and outcomes responses. Two statistical analyses were conducted after the fact. First, we performed the Harman's one factor test using the non-rotated principal component analysis in IBM SPSS. The analysis showed that the first factor accounted for only 33.8% of the variance indicating that an individual factor alone cannot provide the explanation for most of the variability in the assessed constructs (Podsakoff et al., 2003). Second, the Common Latent Factor (CLF) was created in IBM SPSS AMOS by introducing an unmeasured common factor to 16 indicators. By comparing the values obtained in the basic measurement model and CLF model, we concluded that methods variance here was equal to 4.3 %. Therefore, the results of these assessments indicate that common method bias was not responsible for the changes in variables.

3.4 Data Analysis Strategy

In this study, data analysis was carried out using a two-stage Structural Equation Modelling approach employing IBM SPSS Statistics version 28 and IBM SPSS Amos version 28. SPSS was used for screening the data and calculating descriptive statistics and conducting preliminary checks on the dataset while Amos was used for Confirmatory Factor Analysis (CFA) along with assessments of both the measurement model and the structural model.

In the initial phase, the measurement model was examined by way of CFA to verify the reliability and validity of the four latent constructs. Reliability for internal consistency was determined based on the estimated value of Cronbach alpha and Composite Reliability (CR). Only values of .70 and above were regarded as satisfactory. Convergent validity was assessed using standardized regression loadings and Average Variance Extracted (AVE). Thus, loadings of around .60 or higher and AVE values of .50 or above were treated as acceptable. In the end, discriminative validity was determined with the help of the Fornell–Larcker criterion and Heterotrait–Monotrait (HTMT) ratios. The model fit was evaluated based on several goodness-of-fit indices (such as chi-square/degrees of freedom ratio, CMIN/DF, Comparative Fit Index, CFI, Tucker–Lewis Index, TLI, RMSEA, and Standardized Root Mean Square Residual, SRMR). In the second stage, the structural model was estimated to examine the hypothesized direct relationships among GAIL, SOR, SESE, and SII. Hypotheses H1–H5 were evaluated using standardized path coefficients (\beta), critical ratios (CR), and associated significance levels. The two mediators were entered simultaneously to estimate the proposed parallel mediation model. The indirect effects corresponding to H6a (GAIL → SOR → SII) and H6b (GAIL → SESE → SII) were assessed using bias-corrected bootstrapping with 5,000 resamples and a 95% confidence interval in AMOS. A mediation effect was considered statistically significant when the corresponding confidence interval for the indirect effect did not include zero.

4. Empirical Results:

4.1 Measurement Model Assessment and Confirmatory Factor Analysis

Prior to structural path modeling, a full-measurement Confirmatory Factor Analysis (CFA) incorporating all 16 manifest indicators across the four latent constructs was executed using Maximum Likelihood estimation in AMOS v.28. The initial measurement model demonstrated excellent goodness-of-fit to the empirical data ($N = 550$):

$\chi^2 = 214.38$, $df = 98$, $\chi^2/df = 2.188$ (well below the threshold of 3.0); CFI = .981 ; TLI = .977 ; SRMR = .032 ; and RMSEA = .047 (90% CI [.038, .055]). All fit indices comfortably exceeded the recommended cut-offs (CFI,TLI ≥ .95; SRMR ≤ .08; RMSEA ≤ .06) established by Kline (2016) and Hair et al. (2019).

Prior to structural path analysis, a complete measurement batch Confirmatory Factor Analysis (CFA) using all 16 observed signals from the four underlying constructs was conducted through Maximum Likelihood estimation in AMOS v.28. The result is a phantastic measurement model that fits the data well (N = 550): χ2 = 214.38, df = 98, χ2/df = 2.188 which is much lower than 3.0; CFI = 0.981; TLI = 0.977; SRMR = 0.032; and RMSEA = 0.047 (90% CI [.038, .055]). All other fit indices also passed the thresholds set by Kline (2016) and Hair et al. (2019) with ease (CFI, TLI ≥ 0.95; SRMR ≤. 008; RMSEA ≤. 0.06).

Construct reliability and convergent validity were assessed through standardized factor loadings (λ), Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). The detailed results in Table 1 showed that all standardized factor loadings were between .742 and .889, which were higher than the recommended level of .60 and were statistically significant (p < .001). Moreover, there was evidence of internal consistency, as Cronbach's alpha and Composite Reliability values for all the constructs were greater than the accepted threshold of .70 (values were in the range of .858 and .914). The convergent validity of all the constructs was confirmed, as the AVE values for each latent variable exceeded the threshold of .50 (values in the range of .602 and .727).

Table 1: Confirmatory Factor Analysis, Reliability, and Convergent Validity Estimates ($N = 550$)

Construct & Item Indicators	Unstandardized (β)	Std. Error (SE)	Critical Ratio (t-value)	Std. Loading (λ)	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Generative AI Literacy (GAIL)					0.882	0.883	0.654
GAIL1: Conceptual understanding	1	—	—	0.782			
GAIL2: Prompting & evaluation	1.042	0.043	24.232	0.835			
GAIL3: Ethical & footprint literacy	0.968	0.042	23.048	0.791			
GAIL4: Problem-solving workflow	1.025	0.042	24.405	0.826			
Social Opportunity Recognition (SOR)					0.858	0.859	0.603
SOR1: Spotting unmet social needs	1	—	—	0.742			
SOR2: Connecting needs with tech	1.058	0.051	20.745	0.789			
SOR3: Evaluating venture viability	1.021	0.05	20.42	0.768			
SOR4: Identifying public value	1.082	0.051	21.216	0.806			
Social Entrepreneurial Self-Efficacy (SESE)					0.891	0.893	0.676
SESE1: Starting & managing initiative	1	—	—	0.801			
SESE2: Mobilizing resources & peers	1.034	0.041	25.22	0.842			
SESE3: Coping with risk & uncertainty	0.989	0.041	24.122	0.812			
SESE4: Leveraging tools to scale impact	1.031	0.041	25.146	0.833			
Social Innovation Intention (SII)					0.912	0.914	0.727

SII1: Intention to launch/join enterprise	1	—	—	0.828			
SII2: Making concrete plans for problems	1.045	0.038	27.5	0.865			
SII3: Pursuing measurable social impact	1.071	0.038	28.184	0.889			
SII4: Executing SDG-aligned projects	0.998	0.038	26.263	0.826			

[a] Fixed parameter for scale identification. All factor loadings are significant at $p < .001$.

To verify the reliability of the discriminant validity, two methods were employed. The first one is called the Fornell-Larcker criterion. According to it, it was confirmed that the values of the square root of the AVE are bigger than the inter-construct correlations (presented in Table 2). Another method used to verify discriminant validity is the Heterotrait-monotrait approach. The correlation ratios under it vary between .382 and .614 and are still well below the propounded .85 threshold value (Henseler et al., 2015).

Table 2: Discriminant Validity Assessment: Fornell–Larcker Criterion and HTMT Ratios

Construct	GAIL	SOR	SESE	SII
Generative AI Literacy (GAIL)	0.809	0.421	0.488	0.512
Social Opportunity Recognition (SOR)	0.368	0.777	0.523	0.588
Social Entrepreneurial Self-Efficacy (SESE)	0.425	0.448	0.822	0.641
Social Innovation Intention (SII)	0.452	0.512	0.564	0.853

Off-diagonal elements below the diagonal are inter-construct correlations. Diagonal bold values represent the square root of AVE. Off-diagonal elements above the diagonal are HTMT ratios. All correlations are significant at $p < .001$.

4.2 Structural Model Assessment and Direct Hypothesis Testing

The structural equation model was then determined using AMOS v.28 in order to test hypotheses H_1 through H_5 after the verification of measurement. The structural model was found to fit the data well with $\chi 2 = 214.38$, df=98, $\chi 2/df = 2.188$, CFI = 0.981, TLI = 0.977, SRMR = 0.032, RMSEA = 0.047 (90% CI [0.038, 0.055]). The model explains 18.1% of the variability in Social Opportunity Recognition ($R^2 = 0.181$), 23.5% of the variability in Social Entrepreneurial Self-Efficacy ($R^2 = 0.235$) and 42.8% of the total variability in Social Innovation Intentions ($R^2 = 0.428$).

Table 3 Structural Model Path Coefficients and Direct Hypothesis Testing (N = 550)

Hypothesis & Structural Path	Unstandardized (β)	SE	Critical Ratio (t-value)	Standardized Path (β)	p-value	Result
H1 : GAIL→SII (Direct Effect)	0.182	0.042	4.333	0.185	<.001	Supported
H2 : GAIL→SOR (Cognitive Antecedent)	0.425	0.048	8.854	0.425	<.001	Supported
H3 : SOR→SII (Cognitive Outcome)	0.321	0.045	7.133	0.302	<.001	Supported
H4 : GAIL→SESE (Agentic Antecedent)	0.485	0.046	10.543	0.485	<.001	Supported
H5 : SESE→SII (Agentic Outcome)	0.398	0.044	9.045	0.388	<.001	Supported

Table 3 indicates support for all direct hypotheses. The effect of Generative AI Literacy is positive in regard to Social Innovation Intentions (H_1: β = 0.185, t = 4.333, p < 0.001). The relational direct paths show that GAIL predicts Social Opportunity Recognition (H_2: β = 0.425, t = 8.854, p < 0.001) and Social Entrepreneurial Self-Efficacy (H_4: β = 0.485, t = 10.543, p < 0.001). Likewise, it is important to note that SOR (H_3: β = 0.302, t = 7.133, p < 0.001) and SESE (H_5: β = 0.388, t = 9.045, p < 0.001) lead to statistical prediction of Social Innovation Intentions.

4.3 Parallel Mediation Analysis (H_{6a} and H_{6b})

To carry out the official examination of the indirect mediation processes (H_{6a} and H_{6b}), sentiments defined by the user were calculated in conjunction with bias-corrected bootstrapping with 5000 resample at confidence level of 95% in AMOS v.28.

Table 4: Bootstrapped Specific Indirect Effects and Parallel Mediation Estimates

Specific Indirect Path	Point Estimate	Std. Error (SE)	95% Bias-Corrected CI Lower Bound	95% Bias-Corrected CI Upper Bound	Two-Tailed p-value	Result
Total Indirect Effect (GAIL→SII)	0.316	0.032	0.256	0.382	<.001	Supported
H6a (Cognitive Path): GAIL→SOR→SII	0.128	0.024	0.085	0.18	<.001	Supported
H6b (Agentic Path): GAIL→SESE→SII	0.188	0.027	0.139	0.245	<.001	Supported

The results shown in Table 4 indicates the presence of total indirect effect of GAIL on SII acting through both mediation processes. "Point estimate = 0.316, $p < 0.001$, 95% CI is [0.256, 0.382].

H_{6a} (Cognitive Mediation): The specific indirect effect of Generative AI Literacy on Social Innovation Intentions via Social Opportunity Recognition was found to be significant. "Point estimate = 0.128, $p < 0.001$." Since the 95% bias-corrected confidence interval [0.085, 0.180] does not include zero, H_{6a} is supported.

H_{6b} (Agentic Mediation): Similarly, the specific indirect effect of Generative AI Literacy on SII via Social Entrepreneurial Self-Efficacy was also positive and significant. "Point estimate = 0.188, $p < 0.001$, 95% CI is [0.139, 0.245].

The fact that the direct effect (H_1: $\beta = .185$, $p < 0.001$) was statistically significant even in the presence of the mediation model shows that complementary partial parallel mediating condition exists.

5. Discussion and Implications:

5.1 Discussion of Empirical Findings

The main aim of this research was to investigate the two-fold mechanism by which Generative AI Literacy (GAIL) leads to Social Innovation Intentions (SII) among undergraduate students and incubates in an emerging economy context (N = 550). Using Cognitive Adaptability / Opportunity Identifying theory (the cognitive path) and Social Cognitive theory (the agency path) as the theoretical frameworks for this study, the findings demonstrate the fact that Generative AI Literacy serves as a significant multi-dimensional enabler for social venture creation processes.

Firstly, The relationship between GAIL and SII (H_1: $\beta = 0.185$, $p < 0.001$) has been empirically proved, showing that practical knowledge and understanding of how effective generative tools should be utilized for solving tasks help individuals to develop the intention to launch social ventures. Second, the structural model validated the direct pathways for both components. GAIL had a strong positive effect on SOR (H_2: $\beta = 0.425$, $p < 0.001$), thereby confirming that generative AI acts as a cognitive enhancer promoting an individual's capability of identifying the unmet needs in society and creating solutions based on technology. In addition, SOR exerted a significant influence on SII (H_3: $\beta = 0.302$,$p < 0.001$), proving that cognitive detection of generating public value is a direct precursor for behavioral intentions. At the same time, GAIL had a strong influence on SESE (H_4: $\beta = 0.485$,$p < 0.001$) demonstrating that the knowledge of technical and operational aspects of AI technologies providing mastery experiences necessary for the development of domain-specific self-efficacy. After that, SESE led to SII (H_5: $\beta = 0.388$,$p < 0.001$) confirming the agentic position of self-belief in the possibility of performing difficult business tasks and using resources for innovative purposes. Thirdly - and perhaps most crucially - a bootstrap approach to parallel mediation analysis (including 5,000 iterations) was able to confirm the existence of specific indirect effectiveness mechanisms used in the process and validate the fact of complementary partial parallel mediation. Both the message towards the cognitive path via SOR (H_{6a}: point estimate = 0.128, $p < 0.001$, 95% CI [0.085, 0.180]) and the message towards the agentic process via SESE (H_{6b}: point estimate = 0.188, $p < 0.001$, 95% CI [0.139, 0.245]) were found to be statistically significant. It should be noted that the second parameter – measuring the message regarding the agentic process through SESE – was slightly greater than the first one, indicating that while cognitive opportunity recognition is essential, the enhancement of the innovator's psychological confidence and self-efficacy when it comes to the realization and implementation of digital social innovations appears to be a more powerful mechanism influencing the correspondence between AI literacy and social innovation intentions.

5.2 Theoretical Contributions

This research presents three noteworthy insights into the bodies of work within artificial intelligence, cognitive entrepreneurship, and social innovation.

An extensive review of literature around the application of AI in higher education and entrepreneurship activity points out that technological adoption has been predominantly examined through single-stream approaches such as

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). However, this research applies a two-way approach to show that generative AI literacy plays a dual role as a cognitive processor (improving problem framing and pattern recognition according to the theory of cognitive adaptability) and a motivational element (increasing confidence related to task completion on the basis of social cognitive theory).

Previous studies on GenAI did provide some insights into corporate efficiency improvements or academic achievement, but the present paper achieved empirical confirmation of the relationship between GenAI capabilities and impact entrepreneurship. The findings indicate that ethical awareness and ability to prompt and critically evaluate GenAI outputs are not only technical abilities but also basic elements of social entrepreneurship.

Using covariance-based structural equation modeling (by employing IBM SPSS AMOS software), including user-defined sentiments and 5,000 bias-corrected bootstrap resamples, the paper presents a solid methodological approach for the identification of the differing indirect mechanisms without merging them into a single total indirect effect or causing cross-talk between mediators.

5.3 Practical and Policy Implications

These empirical findings produce practical insights for the authorities of higher education institutions, decision makers in the education sector, and head managers of incubators:

- With Respect to Instructors of Higher Education Institutions: Teaching of Artificial Intelligence needs to move from the level of basic user operation instruction to the level of implementation of complex frameworks of AI literacy (including ethical limits, algorithmic bias, and critical evaluation of results). Interdisciplinary hackathons and social entrepreneurship courses should provide explicit attention to prompt engineering as the tools for solving community problems related to sustainability and UN sustainable development goals (SDG).

The empirical insights yield actionable implications for higher education administrators, policy makers, and incubator directors:

- **For University Educators & Curriculum Developers:** Artificial intelligence instruction must evolve beyond basic user operation to incorporate comprehensive AI literacy frameworks (encompassing ethical boundaries, algorithmic bias, and critical evaluation of outputs). Interdisciplinary hackathons and social entrepreneurship courses should explicitly embed prompt engineering and AI workflow integration as foundational tools for solving community-level sustainability and UN SDG challenges.
- **In connection with Incubators and Innovation:** In developing economies, technology business incubators should apply "GenAI-for-Impact" modules in their early-stage acceleration processes. This way, they can help create self-efficacy for social entrepreneurship (SESE), by equipping their potential incubates with AI tool packs for quick prototyping, financial viability modeling, and resource mobilization.
- **For Policymakers:** Policy builders seeking to promote digital social innovation in developing countries should make investments into digital infrastructure projects aimed at making advanced generative AI technologies accessible for youth innovators, linking the technology with formal learning opportunities.

5.4 Limitations and Future Research Directions

Although it has made important contributions to the literature, there are a few limitations that can be mentioned to provide directions for future research. First, this research utilized the cross-sectional design, which does not allow for absolute causal attribution of results in time. Future research should use longitudinal or experimental designs to find how the evolution of GenAI capabilities leads to actual venture creation behaviors beyond intentions. Second, the data was obtained through university students and incubatees in India; while India is the main emerging digital ecosystem, cross-cultural comparative studies across the West, Latin America, or Africa would boost the external validity of the results. Finally, future researchers can expand this framework by introducing some boundary conditions, like individual risk tolerance, institutional support, or technological anxiety as moderating variables (W) of direct and indirect effects.

6. Conclusion

The present research brings forward robust empirical proof of the impressive role of Generative AI Literacy in building the new generation of social innovators in an emerging economy context. The Cognitive-Motivational Dual Mediation Model was developed using evidence obtained from 550 higher education students and incubator incubatees in India, establishing the fact that generative AI literacy does not contribute directly to motives for social innovation but instead achieves its effect through other cognitive mechanisms. More specifically, operational, evaluative and ethical AI skills act simultaneously as cognitive amplifiers, boosting an individual's ability to identify feasible social opportunities, and motivational drives that provide individuals with self-efficacy needed to realize complex social projects. From a methodological perspective, the application of covariance-based structural equation modeling (CB-SEM in IBM SPSS AMOS) utilizing 5,000 bias-corrected bootstrap resamples indicates a state of complementary

partial parallel mediation with the agentic pathway through Social Entrepreneurial Self-Efficacy having the highest indirect effect. This practically implies that enabling the new innovators with generative AI platforms and the appropriate training in prompt engineering and application of ethical principles offers a significant tool for educational institutions and incubators for making social changes. Since the higher education environment aims to use artificial intelligence for good in society, the development of the simultaneous cognitive and agentic abilities of individuals will become crucial for transforming digital literacy into social innovations.

References:

1. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
2. Austin, J. E., & Seitanidi, M. M. (2012). Collaborative value creation: A review of partnering between business and the nonprofit sector. Part I: Value creation spectrum and collaboration stages. Nonprofit and Voluntary Sector Quarterly, 41(5), 726–758. https://doi.org/10.1177/0899764012450777
3. Bacq, S., & Alt, E. (2018). Feeling capable and accountable: Exploring the role of empathy and sense of efficacy in social entrepreneurial intentions. Journal of Business Ethics, 147(1), 109–125. https://doi.org/10.1007/s10551-015-2987-x
4. Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
5. Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.
6. Bandura, A. (2001). Social cognitive theory: An agentic perspective. Annual Review of Psychology, 52(1), 1–26. https://doi.org/10.1146/annurev.psych.52.1.1
7. Banh, L., & Strobel, G. (2023). Generative artificial intelligence in business and management: A systematic literature review and research agenda. Journal of Information Technology, 38(4), 312–338.
8. Baron, R. A. (2006). Opportunity recognition as pattern recognition: How entrepreneurs "connect the dots" to identify new business opportunities. Academy of Management Perspectives, 20(1), 104–119. https://doi.org/10.5465/amp.2006.19873402
9. Bettman, J. R. (1979). An information processing theory of consumer choice. Addison-Wesley.
10. Corner, P. D., & Ho, M. (2010). How opportunities develop in social entrepreneurship. Entrepreneurship Theory and Practice, 34(4), 635–659. https://doi.org/10.1111/j.1540-6520.2010.00382.x
11. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Ji, H., Marsh, I., Modgil, S., Narayanan, S., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
12. Galbraith, J. R. (1974). Organization design: An information processing view. Interfaces, 4(3), 28–36. https://doi.org/10.1287/inte.4.3.28
13. George, G., Merrill, R. K., & Schillebeeckx, S. J. (2021). Digital sustainability and entrepreneurship: How tech entrepreneurs are addressing the UN Sustainable Development Goals. Journal of Management Studies, 58(6), 1668–1703. https://doi.org/10.1111/joms.12698
14. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.
15. 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. https://doi.org/10.1007/s11747-014-0403-8
16. Hockerts, K. (2017). The effect of experiential learning on the development of social entrepreneurial intentions. Journal of Business Venturing, 32(1), 42–55. https://doi.org/10.1016/j.jbusvent.2016.10.001
17. Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.
18. Kong, S. C., Cheung, W. M., & Zhang, G. (2023). Evaluating an artificial intelligence literacy programme for developing university students' conceptual understanding, practical skills, and ethical awareness. Computers and Education: Artificial Intelligence, 4, Article 100132. https://doi.org/10.1016/j.caeai.2023.100132
19. Kraus, S., Niemand, T., Halberstadt, J., Shaw, E., & Syrjä, P. (2017). Social

entrepreneurship orientation: Development of a measurement scale. International Journal of Entrepreneurial Behavior & Research, 23(6), 977–997. https://doi.org/10.1108/IJEBR-07-2016-0206

20. Krueger, N. F., Reilly, M. D., & Carsrud, A. L. (2000). Competing models of entrepreneurial intentions. Journal of Business Venturing, 15(5–6), 411–432. https://doi.org/10.1016/S0883-9026(98)00033-0
21. Mair, J., & Martí, I. (2006). Social entrepreneurship research: A source of explanation, prediction, and delight. Journal of World Business, 41(1), 36–44. https://doi.org/10.1016/j.jwb.2005.09.002
22. Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, Article 100041. https://doi.org/10.1016/j.caeai.2021.100041
23. Ng, D. T. K., Su, J., & Chu, S. K. W. (2024). Generative AI literacy: Definition, framework, and competencies for higher education. Computers & Education, 210, Article 104961.
24. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
25. Saebi, T., Foss, N. J., & Linder, S. (2019). Social entrepreneurship research: Past achievements and future directions. Journal of Management, 45(1), 70–95. https://doi.org/10.1177/0149206318793196
26. Shapero, A., & Sokol, L. (1982). The social dimensions of entrepreneurship. In C. A. Kent, D. L. Sexton, & K. H. Vesper (Eds.), Encyclopedia of Entrepreneurship (pp. 72–90). Prentice-Hall.
27. Simon, H. A. (1962). The architecture of complexity. Proceedings of the American Philosophical Society, 106(6), 467–482.
28. Thompson, E. R. (2009). Individual entrepreneurial intent: Construct clarification and development of an internationally reliable metric. Entrepreneurship Theory and Practice, 33(3), 669–694. https://doi.org/10.1111/j.1540-6520.2009.00321.x
29. Zhao, H., Seibert, S. E., & Hills, G. E. (2005). The mediating role of self-efficacy in the development of entrepreneurial intentions. Journal of Applied Psychology, 90(6), 1265–1272. https://doi.org/10.1037/0021-9010.90.6.1265