OPPORTUNITY RECOGNITION AS A PRECURSOR TO THE ANTECEDENTS OF ENTREPRENEURIAL INTENTION WITHIN THE CONTEXT OF GENDER AND THE UNIVERSITY ENVIRONMENT AND SUPPORT SYSTEM

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Abstract

This study analyzes the relationship between opportunity recognition (OR) and the antecedents of entrepreneurial intention (EI) while exploring gender differences in these relationships within the context of university environment and support System (ESS). A dual-stage approach was used to analyze partial least squares structural equation modelling (PLS-SEM) and structural causal models (SCM). The PLS-SEM revealed significant direct effects of ESS on OR. It also showed a direct effect of OR on the precursors of intention: attitude toward behaviour, subjective social norms, and perceived behavioural control. Finally, the regression revealed gender moderation in the relationship between ESS and OR. Surprisingly, gender did not moderate between OR and the antecedents of entrepreneurship. The SCM further confirmed the direct causal effect of OR on the antecedents of entrepreneurship. More importantly, the current findings suggest that OR could be positioned as a precursor to antecedents of EI. This study was carried out among 389 university students in Atlantic Canada. No study to date has explicitly considered the effect of OR the antecedents of entrepreneurship. Additionally, to the author's knowledge, it is the first study in entrepreneurship to combine PLS-SEM with structural models using extracted latent variable scores.

General Summary

This research aimed to determine whether opportunity recognition precedes the antecedents of entrepreneurial intention—attitude towards behaviour, perceived behavioural control, and subjective social norms—while examining the role of the university environment and support systems. It also investigated whether gender influenced these relationships. The findings showed that the university environment and support systems positively impacted opportunity recognition, which, in turn, had a causal relationship with the three antecedents of entrepreneurial intention. Compared to women, men had a greater likelihood of recognizing opportunities after engaging with the university environment and support systems. However, gender did not affect the relationship between opportunity recognition and the antecedents of entrepreneurial intention. From a policy perspective, the study shows that teaching students how to recognize practical entrepreneurial opportunities fosters interest in entrepreneurship.

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Chapter 1 Background and Introduction

1.1 Background

A resolve toward new venture creation typically characterizes entrepreneurial intention (EI). This resolve manifests as a heightened focus and the allocation of mental resources toward acquiring knowledge necessary for entrepreneurship (Bird, 1988). EI is a planned behaviour because it encompasses specific plans for carrying out entrepreneurial behaviour (Ajzen, 1991). According to the literature, this EI is believed to precede the creation of new ventures (Krueger & Carsrud, 1993). Three established factors lead to the intention and subsequent behaviour to start a venture: attitude toward the behaviour (ATB), which reflects whether the individual perceives the behaviour as enjoyable or worthwhile; subjective social norm (SSN), which concerns whether the individual's social network views the behaviour as desirable; and perceived behavioural control (PBC) which is an individual's belief in their ability and the availability of external resources to implement a behaviour successfully (Ajzen, 1991; Kolvereid, 1996a; Maheshwari et al., 2023).

Another step in the entrepreneurial journey is opportunity recognition (OR). OR involves identifying and evaluating potential business ideas for market exploitation (Krueger, 2000). The literature reviewed shows that individuals pursue entrepreneurship once they recognize opportunities. However, the influence this recognition has on ATB, PBC, and SSN is not very well understood. Specifically, the question is this: can an opportunity be recognized before the EI antecedents take hold? Another overlooked dimension is the role of gender in this dynamic. There is a growing emphasis on increasing gender representation in entrepreneurship to address inequality (Rietveld & Patel, 2022). Despite this emphasis, the literature shows that, even when women recognize opportunities, they are less likely than men to pursue entrepreneurship (Akhtar et al., 2022; Amofah & Saladrigues, 2022; Cavich & Chinta, 2022; Hassan et al., 2020; Ryu & Kim, 2020). This is why, in addition to examining the influence of OR on the precursors to EI, this research will also focus on exploring gender differences in these relationships. This exploration uses a combination of gender schema theory, social learning theory, social identity theory, and stereotype activation theory. Thus, the study ascertains whether the gender moderation in the relationship between OR and EI antecedents can help show if women are less inclined to translate recognized opportunities into venture creation efforts. Therefore, the aim of this study would be the following: First, analyze the direct effect of the university ESS on OR using regression analysis. Second, analyze if OR is a precursor to the antecedents of EI. Third, to understand the gender differences in the relationship between the university ESS and OR. Finally, analyze if there is a gender moderation effect in the relationship between OR and the antecedents to EI.

These inquiries will be addressed using a dual-stage approach: first, through partial least squares structural equation modelling (PLS-SEM), followed by structural causal modelling (SCM). Causal inference using SCM is relevant in the study's context because, in line with conventional wisdom, a relationship between variables does not mean one causes the other (Pearl, 2010). To establish causality, the temporal sequence between two events must be accounted for, which is not ordinarily possible for cross-sectional studies(Cain et al., 2018; López De Prado, 2023). Causal inference supports this analysis in two ways. First, the data structure of a causal graph is specified so that the directionality of the arrows in the graph reflects antecedence (Pearl, 2010). Second, this technique leverages machine learning in simulating interventions (Neal, 2020; Wager, 2020). The ability to simulate interventions in an observational study makes causal inference particularly appropriate for analyzing whether OR is a precursor to EI. This is something that cannot be accomplished with other regression-based techniques. It is true that randomized controlled experiments are the gold standard. However, establishing a controlled environment is often expensive and could require considerable effort. Causal relationships might not be as verifiable as randomized controlled trials; however, combining them with other regression analyses adds a layer of robustness to the study (López De Prado, 2023). Within entrepreneurial research, no study has combined these two methodologies. Combining these methods adds a layer of novelty to the study. This thesis shall follow a manuscript style in distilling the ideas and observations of this study.

1.2 Introduction

1.2.1 University Environment and Support system

The education system comprises institutional structures, policies, and support mechanisms that foster individual knowledge stock (Baron, 2006). It is designed to equip students and stakeholders with the necessary resources for personal development (Carney, 2022; UNESCO, 2020). It also bolsters human capital (Moe & Wiborg, 2016). It is a function of different national policies in that countries differ in their implementations and priorities (Moe & Wiborg, 2016). In line with human capital theory, a solid university system has been linked to national development (DeTienne & Chandler, 2007; Moe & Wiborg, 2016). Those who recognize its role are more likely to prosper (Egorychev et al., 2014). Traditionally, the effectiveness of an university system has been linked to its curricula and advancements (Chai et al., 2013; Harris et al., 2009). However, there has been a recent shift in focus towards the inclusion of support mechanisms (Araya, 2019; Barrenechea et al., 2023; Chai et al., 2013; Farmer et al., 2023; Harris et al., 2009; Kenny & Cirkony, 2022; Sandoval Mena et al., 2019). These support mechanisms encourage students and enhance their sense of innovation and social awareness. As a result, entrepreneurship becomes their natural outlet. Several international organizations, including the World Economic Forum and the United

Nations Conference on Trade and Development (UNCTAD), have identified creating entrepreneurial opportunities as crucial for economic growth (UNCTAD, 2021; Chai et al., 2013). Educational institutions are thus positioned to expose students to entrepreneurship. Some scholars point out that university students could play a pivotal role in job creation (Murphy & Dyrenfurth, 2012). This explains the increasing attention academic researchers in Europe and North America have given student entrepreneurship.

1.2.2 Opportunity Recognition

The entrepreneurial journey is not possible without the process of OR (Ardichvili et al., 2003). According to Shane (2000), OR is the basis of entrepreneurship and is a function of prior knowledge, cognitive processes, social networks, and personality traits. He used this basis to explain why some people start businesses and others do not.

1.2.2.1 Definition and conceptual delineation of opportunity recognition.

Significant progress has been made toward understanding OR in the literature (Ardichvili et al., 2003). However, there are still major points of contention (Kuckertz et al., 2017). This disagreement sometimes manifests in terms of its conceptual definition (Kuckertz et al., 2017) or the process involved (Ardichvili et al., 2003). Regarding its definition, it is often conflated with opportunity identification, opportunity creation (DeTienne & Chandler, 2007), opportunity exploitation (Kuckertz et al., 2017), and perceived opportunity. This study shall adhere to Kuckertz et al. (2017, p. 81) and their validated measure for OR, which defines it as "...being alert to potential business opportunities, actively searching for them, and gathering information about new ideas on products or services.". Unlike perceived opportunity, which is an individual's subjective assessment of the potential for entrepreneurial activities in a given context (Bohlmann et al., 2017), OR is a cognitive process (DeTienne & Chandler, 2007; Liao et al., 2023) that involves the actual generation of business ideas that may result in a viable entrepreneurial offering (Shane & Venkataraman, 2000). This delineation from perceived opportunity is subtle yet important. It is important because, unlike OR, perceived opportunity involves an individual's evaluation alone (Bohlmann et al., 2017). Opportunity exploitation is the process that follows after opportunity recognition (Kuckertz et al., 2017). It involves concrete activities culminating in the creation of a tangible business. The difference between recognition and exploitation is that there is no need to make an effort toward the venture creation process in recognition. The diminishment in the need for venture creation makes the intended population (students) suitable for this study.

1.2.2.2 Entrepreneurial Theories of Opportunity:

Economic theories used in the study of opportunity recognition:

The discourse surrounding OR in economic theory gained substantial traction following the seminal work of Schumpeter (1934). In his contribution, Schumpeter expounded on how to market innovation continuously renders obsolete, outdated models in a perpetual cycle of simultaneous creation and destruction. The entrepreneur was introduced as the agent who initiated this process, aiming to exploit the discrepancies between potential and existing operational techniques of generating supplementary profit. There are three perspectives on how entrepreneurs treat opportunities: Neoclassical, Austrian, and psychological perspectives, as identified by and discussed by Shane (2000).

Neoclassical theory: The neoclassical theory posits a market in a state of equilibrium, where supply and demand harmoniously balance, and prices accurately mirror the intrinsic value of goods and services (Shane, 2000; Short et al., 2010; Kirzner 1979). Within this framework, opportunities, considered rare occurrences, arise most likely from external shocks or shifts in the market dynamics, such as technological innovations, demographic changes, or policy alterations (Shane, 2000; Short et al., 2010). Entrepreneurs, depicted as rational actors, leverage their prior knowledge and information to identify and assess opportunities. The anticipation of potential profitability guides these entrepreneurs (Kirzner, 1979; Shane, 2000; Short et al., 2010). Neoclassical theory frames the role of OR in entrepreneurship as intimately linked to market efficiency and the allocation of resources (Baron, 2006; Kirzner, 1979; Langowitz & Minniti, 2007; Shane, 2000; Shane & Venkataraman, 2000; Short et al., 2010).

Austrian theory challenges the neoclassical notion of market equilibrium, asserting that the market is a dynamic and intricate process characterized by constant discovery and coordination (Kirzner, 1979; Shane, 2000). Within this paradigm, opportunities abound, emerging from market participants' imperfect and dispersed knowledge (Kirzner, 1979; Shane, 2000). Entrepreneurs are portrayed as vigilant individuals who actively perceive and seize opportunities by crafting innovative combinations of resources and presenting novel solutions to customer challenges (Kirzner, 1979; Shane, 2000). The Austrian theory places significant emphasis on the pivotal role of OR in entrepreneurship, framing it as a continuous process of both market discovery and creation (Ardichvili et al., 2003; Kirzner, 1979; Langowitz & Minniti, 2007; Shane, 2000; Shane & Venkataraman, 2000; Short et al., 2010)

The Austrian perspective on OR resonates well with the context of this study. In this perspective, ESS fosters unique knowledge stocks that drive information asymmetry. This information asymmetry creates a scenario where some individuals are more alert than others to overlooked market demands (Baron, 2006). Thus, individuals may interpret these market signals more actively. This will foster EI antecedents because their unique knowledge stock will improve confidence in internal and external factors. It will also push them towards a social circle where this is welcome. The information asymmetry makes the Austrian perspective more relevant than the neoclassical perspective, as equilibrium in information access would mean equal opportunity for entrepreneurial action. Yet, other factors ensure that only some become entrepreneurs.

The Austrian perspective also finds an alignment with this study in terms of gender. From here, it could be inferred that gender roles may lead to different career preferences, creating information asymmetry. This could determine whether gender influences OR and moderates its relationship with EI antecedents. Empirical evidence supporting this point will be discussed in the following sections.

1.2.2.3 Psychological theories used in the study of opportunity recognition:

According to Mary George et al. (2016) and Shane (2000), this paradigm is based on inherent and "stable" (Shane, 2000, p.449) characteristics unique to certain individuals. Many authors believe that these psychological attributes affect the decision to search for opportunity in the first place (Baron, 2006; Fiet et al., 2013; Shane & Venkataraman, 2000). Shane concisely encapsulates this domain by offering a keen insight into their assumptions in the venture creation process: rather than focusing on information asymmetry, as seen in Austrian economics, they emphasize inherent individual traits and decisiveness in proceeding to commence venture creation. In the overall context of entrepreneurship, this paradigm is examined through cognitive and personality dimensions (Maheshwari et al., 2023).

1.2.3 Theories in venture creation

1.2.3.1 Theory of Reasoned Action

This model, proposed by Fishbein and Ajzen, (1975), aims to connect intention with behaviour. It posits that an individual's intention precedes their behaviour. The model includes two dimensions: ATB and SSN, contributing to intentions (Vallerand et al., 1992). ATB measures whether the individual finds the behaviour enjoyable or worthwhile, while SSN gauges its desirability within the individual‘s social network (Vallerand et al., 1992). The primary focus of this model is on explaining behaviour driven by free will (Hale et al., 2002). However, it faces criticism for disregarding behaviour beyond an individual‘s control or volition (Hale et al., 2002).

1.2.3.2 Theory of Planned Behaviour

Ajzen introduced the theory of planned behaviour in 1991. This model describes the progression from initial intention to a specific behaviour through a conscious decision. It expanded upon Fishbein & Ajzen (1975) theory of reasoned action (Godin & Kok, 1996). It addresses the limitations of the theory of reasoned action, particularly in explaining behaviour influenced by involuntary external psychological stimuli (Chang, 1998; Godin & Kok, 1996). An often-mentioned criticism is its assumption of rational behaviour (Chang, 1998). This assumption of rational behaviour overlooks impulsive behaviours or scenarios requiring heuristic judgment. Another common source of criticism is its inability to account for emotional and habitual factors that influence behaviour (Adams et al., 2022; Paul et al., 2022).

Kolvereid, (1996b) developed a model for entrepreneurial behaviour that emphasizes ATB. According to this idea, an individual‘s inclination towards self-employment rather than a regular job predicts the intention to own a business (Gohmann, 2012; McNally et al., 2016; Vamvaka et al., 2020). However, McNally et al. (2016) observed several issues with Kolvereid’s scale. This included a lack of empirical validation, inconsistent results, and the necessity for a more streamlined version, which they developed.

Liñán and Chen, (2009) viewed Ajzen's model from a psychoanalytic perspective and developed the Entrepreneurial Intention Questionnaire (EIQ). They tested it in a diverse environment, highlighting entrepreneurial perceptions from a cultural standpoint. Their primary contribution was providing a specific instrument to measure EI while incorporating cultural context. Before their work, the model had several limitations, including notable variations among construct measures, potential biases from linear regression models, and weaknesses in the explanatory power of the SSN construct. By employing structural equation modelling techniques, they addressed these issues, and their approach has been widely acknowledged in the literature across various contexts, including studies on academic EI (Akhtar et al., 2022) and the effect of different cultures and values on EI (Moriano et al., 2012).

1.2.3.3 Entrepreneurial Event Theory

The entrepreneurial event theory by Shapero and Sokol (1982) sheds light on how individuals are prompted to pursue entrepreneurial opportunities following a substantial life disruption. This theory posits that most individuals remain on a predetermined life trajectory due to the passivity of their routine life until a significant event disrupts this inertia. This disruption forces individuals encourage individuals to consider alternative paths beyond their current ones. According to the theory, decision-making is shaped by perceived desirability, perceived feasibility, and a willingness to act. Personal characteristics, social norms, and surrounding circumstances influence these factors.

This theory is well-regarded among intention-based models, highlighting the importance of cognitive factors and subjective perceptions in entrepreneurial behaviour. Compared to the theory of planned behaviour, which focuses on stable and rational decision-making influenced by ATB, SSN, and PBC, entrepreneurial event theory emphasizes how major life events can disrupt and influence entrepreneurial intentions. However, the theory has faced critique. Some argue it overemphasizes the role of innovation in entrepreneurship while overlooking the organizational dimensions (Davids, 2017). Another criticism is its disregard for the crucial role of risk-taking in entrepreneurship: by primarily emphasizing the sequence of events, the entrepreneurial event theory might not adequately grasp the intricate and dynamic nature of the entrepreneurial process, especially concerning risk evaluation and management (Davids, 2017; Maheshwari et al., 2023). This limitation could restrict its usefulness and explanatory capability in comprehending the complete range of entrepreneurial activities. In addition, critics also point out that the theory's foundation on perceiving entrepreneurial events in a hindsight-based manner may oversimplify the understanding of these events and fail to capture the nuanced (inter) subjective factors influencing their structure (Krueger, 1993; Maheshwari et al., 2023). Furthermore, while the theory suggests that organizations can generate standardized events, some say this thinking might diminish the richness of experiencing varied and unexpected events (Gries & Naudé, 2021; O'Toole et al., 2021).

1.2.3.4 Expectancy Theory

Victor Vroom proposed the expectancy theory in 1964 (Heneman & Schwab, 1972). According to this theory, an individual's behaviour is influenced by the outcomes they anticipate. This theory consists of three key components: expectancy, the belief that effort results in a favorable performance; instrumentality, the belief that good performance yields rewards; and valence, the value assigned to the anticipated reward (Kominis & Emmanuel, 2007).

According to this theory, individuals are internally motivated by the belief that effort boosts performance. This performance, in turn, leads to favorable outcomes. From a policy standpoint, the theory highlights the importance of matching rewards with performance, ensuring that individuals earn and value such rewards (Vroom et al., 2015).

Gatewood et al. (2002) found that the feedback individuals received about their entrepreneurial ability, whether positive or negative, influenced their expectations regarding future business start-ups. Building upon Gatewood's findings, Ghouse et al. (2019) integrated this insight into their discussion on female entrepreneurial expectations in Oman. They propose that motivation to start a new entrepreneurial venture is driven by expectations influenced by previous exposure to successful entrepreneurship. Expectancy theory has faced criticism for assuming rational decision-making and overlooking individual variations and social influences. Some argue that it oversimplifies human motivation and behaviour with concepts that are vague and challenging to apply in practice, limiting its utility (Isaac et al., 2001).

1.2.4 Gender Theories in Entrepreneurship

Several theories explore entrepreneurship through a gender lens, including social learning theory, stereotype activation theory, social role theory, gender schema theory, and social identity theory.

1.2.4.1 Social Learning Theory

According to social learning theory, individuals acquire behaviours by observing others and through social validation, often resulting in imitation or modelling. Societal rewards or penalties reinforce these behaviours, influencing gender norms and roles (Bandura, 1977; Fischer et al., 1993; Rumjaun & Narod, 2020). In entrepreneurship, traits like financial-mindedness, assertiveness, and risk-taking are traditionally rewarded in men, while women are encouraged toward social awareness, empathy, and cooperation (Eagly & Karau, 2002; Gupta et al., 2008; Jennings & Brush, 2013; Verheul et al., 2012). Manolova et al. (2012) highlighted a potential consequence of the scarcity of female role models to learn from, suggesting that it contributes to a diffused focus among women. In contrast, they view men as more single-minded in pursuing financial gain under this theory.

1.2.4.2 Stereotype Activation Theory

This theory suggests that social signals can activate stereotypes, which individuals unconsciously adopt and apply in their judgments (Devine, 1989). In entrepreneurship, women are often judged against the 'typical' male entrepreneur stereotype, affecting perceptions of leadership suitability and access to investment. Gupta et al. (2009) found that entrepreneurship is associated with masculine traits, and women who identified with these traits showed higher entrepreneurial intentions. Westhead and Solesvik (2016) noted that while entrepreneurship education boosts female self-efficacy, it may not fully counteract societal expectations and gender stereotypes.

1.2.4.3 Social Role Theory

This theory suggests that societal norms influence gender-related roles. In turn, these lead to gender-specific attitudes and behaviours (Eagly & Wood, 2012). Career choices are often influenced by these socially constructed roles rather than biological choices. Men are expected to take on leadership roles involving risk-taking and assertiveness, while women are directed toward collaborative, nurturing roles (Bird & Brush, 2002).

1.2.4.4 Gender Schema Theory

According to this theory, individuals develop cognitive structures known as schemas based on societal perceptions of gender. This schema guides the gender roles with which individuals view themselves and others (Bem, 1981). These gender-based ideas are usually generated from a young age. For example, if entrepreneurship is viewed as a male activity, women will feel it less fitting. While social role theory is external and based on societal expectations, this theory emphasizes internal cognitive frameworks. Emami et al. (2023) used social schema theory to explore the gendered view of social support among 213 Iranian students. The study found that men see social networks as strategic tools for gaining business insights and assessing risks. On the other hand, women who rely more on these networks see them as avenues for validation and emotional support. The authors emphasize the importance of creating entrepreneurial support systems sensitive to these gendered perspectives. This is because these support systems serve as buffers against perceived risk.

1.2.4.5 Social Identity Theory

This theory is one where individuals identify themselves based on their social or demographic group, like gender. This group identification influences self-concept and behaviour (Tajfel, 1979). The theory has three components: social categorization, identification, and comparison. In entrepreneurship, gender identity may impact entrepreneurial inclination, with men more likely to identify with the entrepreneurial role due to its male majority (Leitch et al., 2018; Murnieks et al., 2016). Datta et al. (2022) found that individuals with a masculine identity, regardless of gender, had higher entrepreneurial intentions. They also noted that students with a strong female identity might feel more confident pursuing entrepreneurship when they receive social support through feedback and reinforcement.

Chapter 2 Literature Review

2.1 Interrelationship between Variables

This section will begin by examining the interrelationships between variables to understand how they fit together and to highlight some underexplored relationships.

2.1.1 EI and OR

The link between OR and EI has garnered attention in the past (Shane & Venkataraman, 2000). The consensus is that the ability to recognize opportunities directly impacts EI. This has been substantiated across various contexts (Abdelwahed, 2022; Darden, 2022; Hoang et al., 2022; Hou et al., 2022a; Maziriri et al., 2019; Ruiz-Palomino & Martínez-Cañas, 2021; Tian et al., 2022; Zhuwau, 2022). In fact, OR emerges as a driver or mediator within the literature (Abdelwahed, 2022; Hou et al., 2022a; Tian et al., 2022). This insight sets the stage for examining how targeted interventions to alert individuals to opportunity could foster EI among students.

2.1.2 OR and ATB

The influence of OR on ATB remains somewhat unclear. While ATB has been empirically shown to directly affect OR (Dougherty et al., 2019; Misra & Mishra, 2016), the reverse relationship has received limited attention. Some studies involving OR and ATB have treated ATB as a moderating factor between OR and other outcomes (Nybakk & Hansen, 2008; Anwar et al., 2022), while others have examined these variables independently as predictors (Bouarir et al., 2023). Ng et al. (2021) identified a positive relationship between entrepreneurial opportunities and ATB using PLS-SEM among Malaysian students. However, they used a subset of items from Bateman and Crant (1993) - a larger scale aimed at measuring proactive personality. Beyond being somewhat dated, this adapted scale may suffer from reduced validity and internal reliability. In addition, it was not explicitly developed to measure OR. Given the limited attention the OR-ATB relationship has received, there is room for shedding more light on it.

2.1.3 OR and PBC

Ajzen (2002) identified self-efficacy and perceived controllability as two key dimensions of perceived behavioural control (PBC). Mahmood et al. (2019) emerged as particularly relevant, as they explicitly examined the effects of OR on PBC. Alongside this, the study by Ng et al. (2021) found a relationship between entrepreneurial opportunity and PBC. The OR-PBC relationship can also be inferred from the extensive literature on the positive link between OR and self-efficacy (Anwar et al., 2022; Fearon et al., 2021; Hassan et al., 2020; Loan et al., 2021; Masoomi & Moghaddam, 2021; Ngah et al., 2020; Urban & Galawe, 2019; Yang et al., 2022). In conclusion, while research on the OR-PBC link remains limited, the existing findings offer a foundation for further exploration. Previous studies have used PLS-SEM to assess this relationship, whereas this study will employ a causal model to examine it more rigorously.

2.1.4 OR and SSN

The relationship between OR and SSN remains under-researched at the time of this writing. Xin et al. (2021) discussed this in a conference proceeding as part of a model analyzing the effect of different entrepreneurial models on job creation. However, their model considered the effect of SSN on OR, which is of converse interest in the context of this research. Other studies here considered them independent variables or mediators in a larger model analyzing EI with no explicit relationship established (Bouarir et al., 2023; Sargani et al., 2020; Vafaei-Zadeh et al., 2023). Based on the current literature, the direct and explicit effect of OR on the SSN of students remains to be considered.

2.1.5 ESS and EI:

Although Kraaijenbrink et al. (2010) initially highlighted the scarcity of literature on ESS, recent interest in this area has grown. Both direct and indirect relationships have been studied extensively.

Regarding the direct relationship, some studies have focused on the role of entrepreneurial education (Adelaja, 2021; Soomro & Honglin, 2018), while others have emphasized the impact of support systems (Mensah et al., 2023). All these studies, primarily using regression-based techniques, report a positive association between ESS and EI.

Some studies examining the indirect relationship have solely focused on entrepreneurial education (Al-Ajlouni, 2021; Amofah & Saladrigues, 2022; Malebana & Mothibi, 2023; Silveyra-León et al., 2023; B. A. Soomro & Shah, 2022). Fewer studies have integrated ESS as a whole (Anshori et al., 2021; Bazan et al., 2019). The prevailing finding suggests an indirect relationship between entrepreneurial education and EI. PBC, ATB, and SSN were seen as mediators in these studies, with their hypotheses showing support (Gera et al., 2024; Karimi et al., 2016; Otache, 2020; Sahinidis et al., 2019). Overall, the consensus in the literature confirms both direct and indirect relationships between ESS and EI, with comprehensive empirical evidence supporting these.

2.1.6 ESS and OR

Logically, there are several reasons why ESS should foster OR. One of them is that the education and support provided by universities and other higher educational institutions works towards enhancing the distinct skill and ability of entrepreneurial OR (Baron, 2006; Fei & Shuangyan, 2024). Equally entrepreneurial education provides an individual with a unique knowledge stock to understand market dynamics, monitor industrial trends and exploit market gaps (Baron, 2006; Kuratko, 2005; Neck & Greene, 2011). Empirically, several studies have tried to analyze the relationship between ESS and OR. Most of them have found a positive direct relationship using regression-based analysis. Many focused solely on entrepreneurial education (Karimi et al., 2016; Li et al., 2022; J. Lyu et al., 2024; Silveyra-León et al., 2023; Wei et al., 2019; Xing, 2022). Others incorporated support systems(Liao et al., 2023; St-Jean et al., 2017). Li et al. and Lyu et al. (2022) considered the role of theory and practical based courses. All except Karimi et al. (2016), found a positive relationship between entrepreneurial education and opportunity recognition. Findings by Karimi et al. (2016) contrast those of Silveyra-León et al. (2023). Using a pre-and post-test design, Karimi et al. (2016) used opportunity identification rather than OR. They introduced entrepreneurial education as an intervention but found no significant difference in opportunity identification levels. However, Silveyra-León et al. (2023), applying the same design and intervention, observed a significant increase in OR. Overall, the prevailing evidence shows that ESS foster OR This evidence will be incorporated into the research model.

2.1.7 The Gender difference in OR and EI

The literature consistently indicates that gender moderates the relationship between OR and EI. Theoretical explanations for this include differences in self-perception and confidence (BarNir et al., 2011); structural barriers and biases (Westhead & Solesvik, 2016); disparities in access to resources and networks (Lortie et al., 2017); and the influence of social norms and gender roles (Shinnar et al., 2018). Empirical studies support these theoretical insights.

Most empirical studies report that the relationship between OR and EI is generally stronger in men than in women (Akhtar et al., 2022; Cavich & Chinta, 2022; Hassan et al., 2020; J. Lyu et al., 2024; Ryu & Kim, 2020). Ryu and Kim (2020), however, observed that this phenomenon varies across geographic contexts: countries such as Italy, Switzerland, Poland, Japan, and India exhibit a stronger OR-EI link among men, whereas the United States, Netherlands, France, Sweden, Chile, South Korea, China, Luxembourg, Ireland, and Israel do not. Supporting Ryu and Kim's findings, Hassan et al. (2020) observed this gender moderation effect in India. Cavich and Chinta (2022) further explored this moderation and found it significant in gender.

These findings suggest that women are less likely than men to show intention after recognizing opportunities, a pattern that may reflect varying structural and social factors. This insight will inform the examination of gender differences in the relationship between OR and the antecedents to EI within this study.

2.1.8 The Gender difference in ESS and OR.

Unlike gender differences in the relationship between OR and EI, the gender influence in the relationship between ESS and OR is poorly understood. DeTienne and Chandler (2007) showed that, despite a difference in the mechanism of their opportunity identification processes, there is no gender difference in the innovativeness of opportunity. Other than this finding, the gender difference in the ESS and OR relationship remains ambiguous. Most used gender as a control variable (Hou et al., 2022b; Lyu et al., 2024; Pandow & Omar, 2019). Others considered the direct effect of gender on OR (Li et al., 2022). None of the studies used gender as a moderator in the ESS and OR relationship. Control variables suppress the influence of confounding factors, whereas moderators highlight variations within subgroups and reveal potential boundaries in relationships

(Babyak & Mortenson, 2022). Examining gender as a moderator could prove more insightful in understanding the dynamics of the ESS and OR relationship concerning gender.

2.1.9 Most similar study

Ng et al. (2021) studied the effects of entrepreneurial opportunities and entrepreneurial education on EI, using PLS-SEM, among Malaysian students. While the research question is similar, it differs from this study in several ways. First, unlike Ng et al. (2021), this study incorporates gender as a moderator in the relationship between OR and EI antecedents. Secondly, in addition to using PLS-SEM, this study incorporates a structural causal model. Also, unlike Ng et al. (2021), this study attempts to link education with opportunity recognition.

Furthermore, the questionnaire used in this study was derived from Kuckertz et al. (2017), while that of Ng et al. (2021) was derived from Bateman and Crant (1993). This is important because, unlike the questionnaire by Bateman and Crant (1993), that of Kuckertz et al. (2017) was explicitly developed to measure OR, making it more directly applicable in the context of this study. Additionally, Kuckertz et al.'s recent measure incorporates more recent theoretical insights.

2.2 Structural Equation Modelling

Structural equation modelling (SEM) is an umbrella term for statistical techniques that combine multiple regression and factor analysis to assess relationships among observed and latent variables, often using path analysis(Bollen, 1989; Hancock et al., 2019; Kline, 1994; Streiner, 2006; Ullman, 2006). SEM's capacity of estimating multiple, interconnected dependencies in a single analysis makes it a preferred tool for researchers. It comprises two types of variables: (1) latent variables and (2) observed (manifest) variables. Latent variables represent underlying theoretical constructs and are typically the focus of measurement. In contrast observed variables are measurable quantities, such as temperature, weight, or questionnaire responses in this study. It also includes factor loadings that describe the relationship between latent variables and their indicators and path coefficients that represent the relationships between exogenous and endogenous latent variables and among endogenous variables (Kline, 1994). SEM also includes measurement error terms associated with endogenous and exogenous indicators and disturbance terms, which are errors associated with endogenous latent variables(Bollen, 1989; Kline, 1994). There are also covariances between exogenous latent variables, measurement errors, and disturbances (denoted below by φ, θ, and ψ, respectively). SEM components are divided into two: (1) A measurement model and (2) a structural model (Bollen, 1989; Kline, 1994). A measurement model defines the relationship between manifest variables and latent constructs, as in (2.17-2.18):

$$X = \Lambda_x \xi + \delta \tag{2.1}$$

$$Y = \Lambda_y \eta + \varepsilon \tag{2.2}$$

A structural model represents relationships between latent variables, as in (2.19)

$$\eta = \beta\eta + \gamma\xi + \zeta \tag{2.3}$$

Making reference to (2.17-2.19), X represents indicators of exogenous latent variables (independent latent variables in the model, influenced by other variables); Y represents indicators of endogenous latent variables (dependent latent variables in the model, not influenced by other variables); Λ represents factor loadings (Λ_x for exogenous, Λ_y for endogenous); γ and β represents path coefficients; ζ represents disturbance terms; ξ and η represent latent variables; ε and δ represent measurement error.

Structural Equation Modelling (SEM) can be broadly classified into two main types based on the estimation techniques they use: these are Partial least squares structural equations modelling and Covariance based structural equations modelling.

Partial least squares Structural equations modelling (PLS-SEM): this combines principal component analysis with regression-based path analysis, estimating parameters from a set of linear equations that form a structured model (Hair et al., 2021; Sarstedt et al., 2022). As a non-parametric method, it does not rely on strict statistical assumptions like normality and homoscedasticity (Hair et al., 2011). PLS-SEM is often employed in exploratory research. This is especially when the theoretical foundations of the models are not well-established (Hair et al., 2011). Its appeal lies in its leniency towards distributional assumptions and its suitability for small sample sizes(Hair et al., 2011). However, it is generally considered less powerful than covariance-based structural equation modelling (CB-SEM) in hypothesis testing. A disadvantage of PLS-SEM is that it prioritizes the maximization of explained variance (predictive power) rather than accurately representing the theoretical model. This approach can lead to biased parameter estimates and limit interpretability, especially in complex models or when theoretical precision is essential (Hair et al., 2012). Additionally, PLS-SEM lacks global goodness-of-fit measures comparable to those in covariance-based SEM, making it harder to assess overall model quality (Hair et al., 2012. It utilizes various weighing schemes: the path weighting scheme, which focuses on optimizing path relationships between latent variables and their indicators; the factor weighting scheme, which prioritizes the relationships within latent variables; and finally, the centroid weighting scheme, which is based on correlations between indicators and latent variables (Hair et al., 2021; Sarstedt et al., 2022). It has been used extensively in venture creation research, especially for complex models. About 20% of the studies reviewed within this research context utilized it (Akhtar et al., 2022; Al-Ajlouni, 2021; Amofah & Saladrigues, 2022; Anshori et al., 2021; Gera et al., 2024; Liao et al., 2023; Lim et al., 2023; Lingappa et al., 2020).

Covariance-Based Structural Equation Modelling (CB-SEM): this is a SEM that relies on covariance structures and aims to minimize the difference in covariance matrix between that in the sample and that implied by the model (Hair et al., 2017). CB-SEM is a rigorous way of testing the goodness-of-fit of a theoretical model. This rigor makes it ideal for studies with well-established theoretical frameworks. CB-SEM operates under several key assumptions: observed variables should follow a normal distribution; relationships between variables should be linear; variances associated with residuals should be constant across all levels of measurement (homoscedasticity), and error terms should be independent and uncorrelated with each other (Hair et al., 2017). Various methods can be used to estimate parameters in CB-SEM, including maximum likelihood (ML), generalized least squares (GLS), and weighted least squares (WLS). While ML and GLS assume normality, WLS is employed for non-normally distributed or ordinal data (Byrne, 2013). CB-SEM is a highly suitable tool for testing model fit and specific hypotheses because its stringent assumptions enhance the robustness and reliability of hypothesis testing (Hair et al., 2017). The downside of CB-SEM is its difficulty with complex models; its strict statistical assumptions; and its large sample size requirement (Hoyle, 2015; Kaplan, 2001; Kline, 1994). Most of the papers that implemented it, did so within the context of established theories and relationships (Abdelwahed, 2022; Gielnik et al., 2015; Kickul et al., 2010; Loan et al., 2021; Soni & Bakhru, 2021; B. A. Soomro & Shah, 2022; Ward et al., 2019; Yang et al., 2022).

Both CB-SEM and PLS-SEM assume linearity in all relationships, which can be a significant limitation since real-world relationships are not always linear. Despite the availability of tools to assess non-linearity, many researchers neglect this analysis, ceasing further investigation when no significant relationship is observed and potentially overlooking important non-linear dynamics.

2.3 Methodological Gap

Richter and Tudoran (2024) highlight that in business and management research, most studies combining PLS-SEM with machine learning methods rely on Artificial Neural Networks (ANNs).

This is typically done to capture non-linear relationships. Some studies integrate ANNs prior to the PLS-SEM analysis, while others apply them afterward. Notably, the authors emphasize that Directed Acyclic Graphs (DAGs) for machine learning have been successfully integrated with PLS-SEM in domains such as transportation, intelligent systems, and life sciences. However, this integration remains unexplored in the context of business research. This signals a significant gap in the literature. Furthermore, none of the quantitative studies reviewed in this thesis have applied this combination. This study will implement their proposal on extracting latent variable scores for Bayesian networks. This will be in an effort to add a layer of robustness to the findings.

2.4 Introduction to Structural Causal Models

Causal inference is a mathematical framework often employed in analyzing the relationship between cause and effect (López De Prado, 2023; Pearl, 1998). It achieves this by intentionally changing a variable to analyze how the outcome variable is affected by this change, in a process called simulated intervention (López De Prado, 2023; Pearl, 1998). Causal inference methods, such as counterfactual analysis and do-calculus, use simulated interventions (e.g., the do-operator in causal models) to estimate causal effects by removing confounding influences. Graphs are used to represent assumptions about the underlying nature of a system of interest (Arif & MacNeil, 2023). They shall be the second stage tool in analyzing OR as a factor that leads to the antecedents of EI. No study in entrepreneurial research has combined it with PLS-SEM. It shall be the complementary analytical tool in this study, because of the added robustness in combining both. The preceding text shall offer a concise overview of this concept and its underlying assumptions.

2.4.1 Graphs:

As stated earlier, graphs are the primary data structures used in analyzing causal effects (Pearl, 1998). They use product decomposition to provide mathematical and computational tractable representations (Pearl, 2010). Product decomposition works by breaking down the joint distribution of a set of variables into products of their conditional distributions to reflect their causal structure. The graphs used here are unique graphs called Directed acyclic graphs (DAG). These are graphs pointing in a specific direction and devoid of loops or cycles. Consider the DAG below:

$$X \rightarrow Y \rightarrow Z$$

It could be decomposed as the joint distribution expressed below (Koller & Friedman, 2010; Lauritzen, 2004; T. Lyu et al., 2019; Neuberg, 2003; Pearl, 2010; Spirtes et al., 2000):

$$P(X,Y,Z) = P(X)P(Y|X)P(Z|Y) \tag{2.4}$$

More formally, it can be expressed in 2.5 where χ_i. represents each node and $Pa(\chi_i)$ are the parents of χ_i.:

$$P(\chi_1\chi_2, \dots, \chi_{n)} = \prod_{i=1}^{n} P(\chi_i|Pa(\chi_i)) \tag{2.5}$$

The decomposition above is useful for several reasons: first, it simplifies the analysis and enhances tractability by breaking down the complex distribution into simpler conditional distributions; second, it makes the relationships more explicit; third, it helps analyze the impact of interventions by modifying the relevant conditional distributions (Pearl, 2010).

The direction reflects time flow along the edges. The acyclic nature represents time not flowing backward, symbolizing treatment before effect. For example, if OR is positioned as a precursor to the antecedents, it will be at the leftmost corner of the graph pointing to these (Pearl, 1998). The edge represents the magnitude of the effect one variable inserts on another. The entire graph mathematically represents a joint probability. One reason they are powerful is their ability to simulate different realizations of the treatment variable to understand how this will affect the outcome. This is called counterfactual reasoning (Pearl, 2010).

2.4.2 Interventions:

To analyze the causal effect of a variable A on another variable B, do-calculus is used (Pearl, 2010). This represents a mathematical intervention, where the random variable A is set to a, externally. These are often denoted as $do(A = a)$. More formally the causal effect of A on B is given by the distribution of B after intervening on A) (Pearl, 1998).

$$P\big(B\big|do(A = a)\big) \tag{2.6}$$

This causal effect can sometimes be expressed in terms of observational (non-interventional) distributions. For example, If A and B are not confounded, then there are no unmeasured common causes of A and B. This gives:

$$P\big(B\big|do(A = a)\big) = P(B|A = a) \tag{2.7}$$

When confounders are present, they must be adjusted for by conditioning on these variables, following principles from probability theory. Below, C represents the confounding variables that affect both A and B

$$P\big(B \mid do(A = a)\big) = \sum_{c} P(B \mid A = a, C = c)P(C = c) \tag{2.8}$$

For example, consider the graph:

$$X \rightarrow Y \rightarrow Z$$

The joint distribution is expressed as:

$$P(X,Y,Z) = P(X)P(Y|X)P(Z|Y) \tag{2.9}$$

To find the effect of X on Z, we compute $P\big(Z\big|\, do(X = x)\big)$. Since X affects Z only through Y, we use the following expression:

$$P\big(Z\big|\, do(X = x)\big) = \sum\nolimits_{y} P(Z \mid Y = y)P(Y = y \mid do(X = x)) \tag{2.10}$$

Furthermore, because intervening on X fixes Y by observing X without any external influence, we have

$$P\big(Y\big|\, do(X = x)\big) = P(Z|\, X = x) \tag{2.11}$$

Thus, we can express the effect of X on Z as:

$$P\big(Z\big|\, do(X = x)\big) = \sum\nolimits_{y} P(Z|\, Y = y)P(Y = y \mid X = x) \tag{2.12}$$

The final expression simply means that by marginalizing over Y, we can compute the effect of an intervention on Z by considering all possible ways Y mediates the relationship between X and Z, provided the assumptions of casual inference hold.

2.4.3 Assumptions:

Positivity (Overlap): For any combination of covariates, each treatment level has a non-zero probability of assignment (Pearl, 1998; Rosenbaum & Rubin, 1983). This ensures that within the sample, no subgroup is entirely excluded from any treatment condition, enabling comparisons across all segments of the population. In other words, regardless of individual characteristics, every subgroup has some likelihood of receiving each treatment, allowing for causal effects to be examined across different parts of the population (Neal, 2020; Pearl, 1998).

$$P\big(Y \big| do(T = t)\big) = \sum\nolimits_{w} P(Y \mid T, W) P(W) \tag{2.13}$$

Ignorability (Unconfoundedness): Given a set of covariates, the treatment is independent of the potential outcomes $Y(a)$ (Cheng, 2023; Rosenbaum & Rubin, 1983). In other words, once we condition the covariates, the treatment can be considered random within each subgroup (Wager, 2020). Formally, this is expressed as in 2.14 where $Y(a)$ is the potential outcome if treatment A were set to a, and X is the set of covariates (Pearl, 1998). Note that $\coprod$ denotes d-separation, a terminology is used to express complete independence between variables, given a third set.

:

$$Y(a) \coprod A \mid X \tag{2.14}$$

Faithfulness: This assumption states that the observed conditional independencies in the data are due to the true underlying causal structure and not due to specific parameter values or coincidences (Pearl, 1998; Weinberger, 2018). In essence, this could be expressed in 2.15.

$$A \coprod_G Y \mid Z \Rightarrow A \coprod_p Y \mid Z \tag{2.15}$$

The above simply implies that if variables are conditionally independent in the graph, then they will be conditionally independent in the population (Pearl, 1998; Neal, 2020).

Stable Unit Treatment Value Assumption (SUTVA): This assumption has two parts. First, the outcome of a unit is independent of the treatment of another unit; second, the potential outcomes for a unit under the treatment actually received are the same as the observed outcomes (consistency) (Neal, 2020; Pearl, 1998).

This could formally be expressed as thus:

$$(A = a) \Rightarrow (Y = Y(a)) \tag{2.16}$$

2.4.4 Structural causal models and cross-sectional data

A structural causal model (SCM) with machine learning is suitable for addressing causality in cross-sectional data because it combines domain knowledge with predictive power, overcoming key limitations of purely statistical approaches. Firstly, SCMs use DAGs to encode causal relationships, ensuring that causal inference is based on justified assumptions rather than correlations. This makes them more robust to misspecification. Secondly, SCMs provide systematic methods (e.g., backdoor adjustment, front-door adjustment) to control for confounding, improving causal estimation in observational data. SCMs allow the estimation of counterfactual outcomes, enabling the evaluation of "what-if" scenarios, which is crucial in cross-sectional settings where time-based interventions are absent. However, this could pose as a challenge because it relies on assumptions of unobserved variables that evolve over time (this is why longitudinal study remains relevant).

Chapter 3 Method

3.1 Model Development

3.1.1 ESS and OR:

There are several reasons to infer that the educational system and support (ESS) foster opportunity recognition (OR). First, higher education institutions, including universities, play a crucial role in developing the distinct skills and cognitive abilities required for entrepreneurial OR (Baron, 2006; Fei & Shuangyan, 2024). Additionally, entrepreneurial education equips individuals with a unique knowledge base, enabling them to understand market dynamics, monitor industry trends, and identify exploitable market gaps (Baron, 2006; Kuratko, 2005; Neck & Greene, 2011). Empirical studies have extensively examined the relationship between ESS and OR, with most finding a positive direct association (Karimi et al., 2016; S. Liao et al., 2022; Liao et al., 2023; López-Muñoz et al., 2023; Lyu et al., 2024; Silveyra-León et al., 2023; St-Jean et al., 2017; Wei et al., 2019; Xing, 2022). Based on this evidence, this study proposes that ESS positively influences OR.

H1: There is a positive relationship between ESS and OR.

3.1.2 OR and ATB:

Attitude toward behavior (ATB) refers to an individual's perception of the desirability and feasibility of engaging in entrepreneurial activities (Vamvaka et al., 2020). Several factors influence this perception, including personal traits, past experiences, social environment, and economic conditions (Ajzen & Fishbein, 2002; Vamvaka et al., 2020). Opportunity recognition plays a crucial role in shaping ATB by influencing how individuals perceive the potential benefits and feasibility of entrepreneurial engagement. When individuals identify an opportunity, they are more likely to view entrepreneurial behavior as valuable and achievable, increasing their motivation to pursue it. This recognition fosters a more positive attitude toward the behavior, as individuals evaluate potential rewards and align their actions with their personal or professional aspirations. The clearer the opportunity and its alignment with individual goals, the stronger the positive attitude toward engaging in the associated behavior. This argument is further supported by Ng et al. (2021), who highlight the impact of entrepreneurial opportunity on ATB. Therefore, the following is proposed:

H2: OR will directly influence ATB, positively.

3.1.3 OR and SSN

SSN serves as implicit guidelines that individuals within a community adhere to (Cialdini & Trost, 1998). These norms are influenced by the perception of others' actions (descriptive norms) and the perception of social expectations (injunctive norms) (Cialdini et al., 1991). Conforming to these norms typically leads to social acceptance, while breaking them can result in social exclusion (Cialdini & Goldstein, 2004). Such norms are essential in shaping our career choices. When individuals recognize more opportunities in entrepreneurship, they are likely to interpret these opportunities within the context of their perceived social norms (Fayolle & Gailly, 2015). If entrepreneurship is seen as a socially acceptable and desirable career within their community or social group, these individuals will be more inclined to pursue it (Krueger et al., 2000). Given this, it is proposed that:

H3: OR directly influences SSN, positively.

3.1.4 OR and PBC

OR, a crucial aspect of entrepreneurship, is significantly influenced by cognitive processes, prior knowledge, and education (Mary George et al., 2014; Filser et al., 2023). These factors shape an individual’s ability to identify and seize potential business ventures. PBC is an individual's belief in their ability and the availability of external resources to implement a behavior successfully. It has both internal and external aspects. Internal aspects include personal skills and determination, while external aspects encompass resources, support, and opportunities (Kiriakidis, 2017; Zolait, 2014). OR can influence PBC by enhancing an individual's belief in their ability to act on the recognized opportunity. When individuals identify an opportunity, they may also assess their own resources, skills, and external factors that could either facilitate or hinder their ability to pursue venture creation. If they believe they have the necessary capabilities or that obstacles can be overcome, their PBC will increase. Conversely, if they perceive significant barriers or lack the required resources, their PBC may be lower. OR helps individuals form a clearer understanding of the feasibility of taking action, thus directly shaping their confidence in their ability to pursue the opportunity and exert control over the desired behavior. In light of this, the following is proposed:

H4: OR directly influences PBC, positively.

3.1.5 Direct effect of SSN on PBC and ATB.

The influence of SSN extends beyond shaping EI among students; it also plays a direct role in determining their ATB and PBC. This has been established within the theory of planned behaviour (Autio et al., 2001; Bazan, 2022; Liñán & Chen, 2009; Shapero & Sokol, 1982). SSN influences ATB positively because individuals who perceive strong social support for entrepreneurship are more likely to develop a positive attitude toward starting a business. In other words. positive reinforcement from peers, mentors, and family fosters the belief that entrepreneurship is a desirable and rewarding career path, enhancing ATB. SSN influences PBC by shaping individuals' beliefs about their entrepreneurial capability. A supportive social environment offers resources, guidance, and encouragement, reinforcing individuals' perception of control over entrepreneurial actions. When individuals trust that their social network will help them navigate challenges, they develop a stronger sense of self-efficacy and perceive fewer obstacles in their entrepreneurial journey. This heightened PBC increases their likelihood of forming entrepreneurial intentions. Given these relationships, it is proposed that higher levels of SSN will lead to more favorable attitudes toward entrepreneurship and an increased sense of perceived behavioral control. Therefore, the following is hypothesised:

H5: SSN directly influences PBC.

H6: SSN directly influences ATB.

3.1.6 EI and its antecedents

The final set of hypotheses shall be in line with the theory of planned behaviour by Ajzen (1991). Based on this theory it is established that the entrepreneurial intention (EI) of students is significantly influenced by attitude toward behaviour ATB, PBC, and SSN. ATB reflects students' positive evaluations and perceptions of entrepreneurship, which directly bolsters their intent to engage in entrepreneurial activities (Ajzen, 1991). PBC, representing the perceived ease or difficulty of performing entrepreneurial tasks, enhances students' confidence in their capacity to pursue entrepreneurial endeavours, thereby positively influencing their EI (Krueger et al., 2000). Additionally, SSN encompasses the support from family, friends, and academic networks. SSN plays a crucial role in reinforcing students' EI by providing the necessary resources, encouragement, and opportunities (Liñán & Chen, 2009). These factors—ATB, PBC, and SSN—serve as antecedents of students' EI. However, the direct effect of SSN on EI was not corroborated by Bazan (2022). Despite this exception, this study shall hypothesize in line with the foundational theories such as Shapero's entrepreneurial event model (Shapero & Sokol, 1982) and the theory of planned behaviour in suggesting that SSN significantly influences ATB and PBC. Therefore, the following hypothesis shall still be proposed:

H7: ATB directly influences EI, positively.

H8: SSN directly influences EI, positively

H9: PBC directly influences EI, positively.

3.1.7 Gender Moderation in the relationship between OR and ESS

The educational system significantly influences individuals' cognitive development, self-efficacy, and ability to identify entrepreneurial opportunities. However, research indicates that educational support does not impact opportunity recognition (OR) equally across genders, as sociocultural norms, differences in self-efficacy, and varying exposure to entrepreneurial role models create disparities (Shinnar et al., 2018). Educational initiatives often include mentoring, networking, and resource access, all of which contribute to OR. Yet, men tend to derive greater benefits from these support mechanisms due to wider access to entrepreneurial networks and the predominance of male role models in the field (Arenius & Minniti, 2005). Brush et al. (2019) highlighted that female entrepreneurs frequently encounter structural barriers that hinder their ability to fully capitalize on educational resources, leading to a comparatively weaker influence on OR. Similarly, Verheul et al. (2012) observed that although both men and women may receive similar entrepreneurial training, men are more likely to view entrepreneurial careers as viable, largely due to their greater exposure to male-dominated entrepreneurial ecosystems. This suggests that educational support has a stronger effect on OR for men. Therefore, the following is proposed:

H10: The relationship between ESS and OR will be more pronounced in men compared to women.

3.1.8 Gender Moderation in the relationship between OR and ATB

The reviewed literature consistently shows a negative gender moderation effect between OR and EI for women (Akhtar et al., 2022; Cavich & Chinta, 2022; Hassan et al., 2020; Ryu & Kim, 2020), suggesting that women are less likely to act on recognized opportunities than men. However, the gender moderation in the relationship between OR and ATB is not well understood. Social identity theory, social learning and social role theory suggest a gender-specific response toward ATB (Camelo-Ordaz et al., 2016; Datta et al., 2022; Manolova et al., 2012; Eagly & Karau, 2002). Financial success and freedom are key motivators for entrepreneurship, which is often seen as a masculine pursuit (Datta et al., 2022). Social learning theory highlights societal judgment associated with deviating from traditional social roles. Empirical studies using social learning theory also show that women are less motivated by financial success and freedom than men (Manolova et al., 2012). This is because freedom is viewed as contrary to communal roles typically associated with women who are less enthusiastic about deviating from these roles (Eagly & Karau, 2002; Eagly & Wood, 2012; Tsai et al., 2016b). Therefore, the following is proposed:

H11: Among women, the relationship between OR and ATB is weaker than among men.

3.1.8 Gender Moderation in the relationship between OR and SSN

Gender influences an individual's perception of and response to entrepreneurial opportunities, as well as their interpretation of the social expectations tied to these opportunities (Gupta et al., 2008; Eddleston & Powell, 2008). This can be explained by gender schema theory and stereotype activation theory (Cliff et al., 2005; Eddleston & Powell, 2008; Emami et al., 2023). Studies suggest that men and women often experience different levels of social support and face varying societal expectations regarding entrepreneurship (Eddleston & Powell, 2008; Emami et al., 2023). These differences in social support can influence how individuals internalize the subjective social norms associated with pursuing entrepreneurial ventures (Gupta et al., 2008; Emami et al., 2023). Compared to women, men are often more likely to recognize and act on entrepreneurial opportunities in environments that reinforce entrepreneurial activity (Emami et al., 2023). This reflects societal norms that traditionally associate entrepreneurship with masculine traits (Ahl, 2006; Eddleston & Powell, 2008). Consequently, gender may moderate the relationship between opportunity recognition and subjective social norms, leading to gender-specific variations in entrepreneurial intentions.

H12: The relationship between OR and SSN is more pronounced in men than women.

3.1.9 Gender Moderation in the relationship between OR and PBC

Gender differences in socialization and access to resources can influence how men and women perceive their control over entrepreneurial endeavors (Emami et al., 2023; Westhead & Solesvik, 2016). Empirical studies using social learning and stereotype activation theories have shown that women exhibit lower self-efficacy in entrepreneurial pursuits than men (Manolova et al., 2012; Westhead & Solesvik, 2016). This is due to challenges in accessing financial resources, networks, and role models (Manolova et al., 2012; Marlow & Patton, 2005). Therefore, gender may influence the extent to which opportunity recognition translates into perceived behavioral control, with this relationship potentially being stronger for men than for women.

H13: The relationship between OR and PBC is more pronounced in men than women.

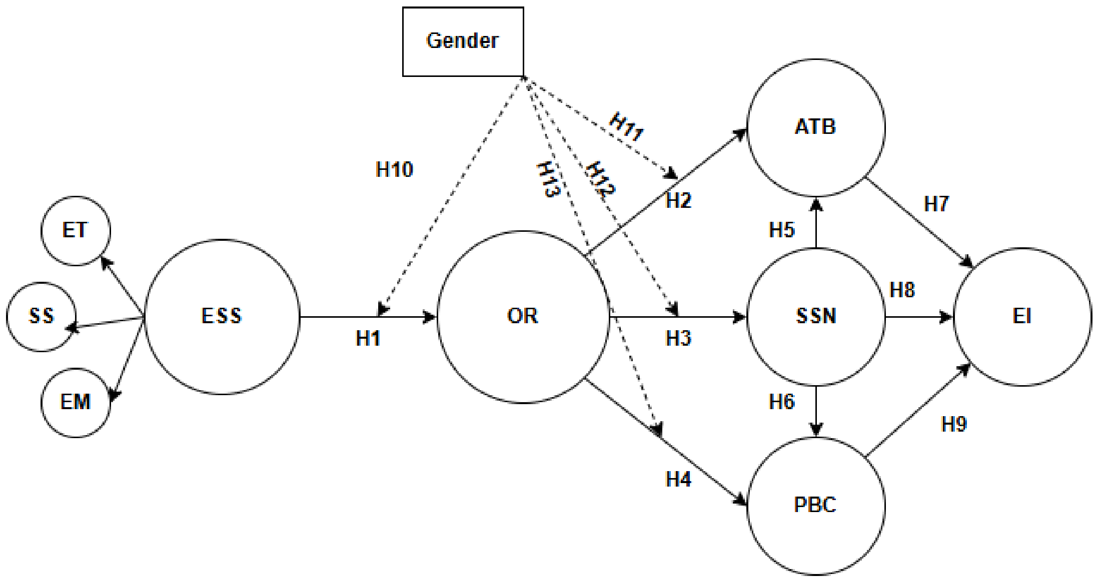

Figure 1 Structural Equation Model

3.2 Tools and overview of procedure

3.2.1 Analytic Tools

We utilized several software packages for data analysis, including SPSS v25 (IBM, 2022), SmartPLS v3.3.3 (Ringle et al., 2014); Python libraries such as DoWny (Sharma & Kiciman, 2020), scikit-learn, and causal-learn; R libraries such as cSem and cSem-DGP for the Monte-Carlo simulation of the path model (Schamberger, 2023).

3.2.2 Overview of procedure

The study employed PLS-SEM to conduct regression analyses, estimate parameters, and derive latent variable scores. It also followed Richter & Tudoran's (2024), recommendations regarding the use of machine learning techniques in a dual-stage method: latent variable scores were extracted using SmartPLS for subsequent analyses in the causal model. Python's DoWhy library was the tool of choice for the causal model (Sharma & Kiciman, 2020). It was used to analyze the effect of OR on the precursors to the antecedents of EI in a causal model. The process involved model specification, identification, estimation, refutation, and sensitivity analysis - all carried out using this library. Detailed use of these procedures is provided in section 2.4. The code and associated outputs are available in Appendix 3.

3.2.2.1 Scholarly debate on the validity of PLS-SEM

There is an ongoing debate, between Rönkkö and Evermann (2013), who question the validity of the technique, and Henseler et al. (2014) who offers a rebuttal. Here is a summary of the issues in the debate.

Measurement Model Validation: Rönkkö and Evermann (2013) argued that PLS-SEM's focus on composite constructs might lead to biased estimations when the research goal is to model common factors. They suggested that PLS-SEM may not effectively validate measurement models intended to represent latent variables. In response, Henseler et al. (2014) contended that PLS-SEM is suitable for analyzing both composite and common factor models, especially when the primary objective is prediction rather than confirmation.

Hypothesis Testing Limitations: Rönkkö and Evermann (2013) highlighted concerns about the statistical foundation of PLS-SEM for null hypothesis significance testing, suggesting it may be less reliable for confirmatory research. Henseler et al. (2014) acknowledged these concerns but introduced advancements such as consistent PLS and confirmatory composite analysis to enhance PLS-SEM's capability for confirmatory purposes.

Sample Size Considerations: While it is commonly believed that PLS-SEM is advantageous for small sample sizes, Rönkkö and Evermann (2013) argued that insufficient samples could compromise the stability and reliability of PLS estimates. Henseler et al. (2014) agreed that larger sample sizes are preferable but maintained that PLS-SEM can still provide reliable estimates with smaller samples, particularly when models are correctly specified.

Measurement Error Concerns: The critique suggested that PLS-SEM might not adequately account for measurement errors, potentially leading to inaccurate parameter estimates. In their rebuttal, however, Henseler et al. (2014) argued that PLS-SEM can effectively handle measurement error through appropriate model specification and the use of consistent PLS estimators.

Exploratory vs. Confirmatory Use: Rönkkö and Evermann (2013) challenged the suitability of PLS-SEM for exploratory research, arguing that its application may be more restricted than commonly assumed. In contrast, Henseler et al. (2014) defended PLS-SEM as appropriate for both exploratory and confirmatory research, particularly when the focus is on theory development and identifying key driver constructs.

3.2.2.2 Rationale Regarding methodological choice

In light of this debate, this study shall adopt PLS-SEM because the study involves complex relationships with a relatively small sample size. PLS-SEM is also flexible with its distributional assumptions. Furthermore, PLS-SEM is well-suited for exploratory analysis, especially when examining relationships that have not been empirically established. For example, the gender moderation within this model and the relationship between OR and EI antecedents are poorly understood in the literature. These factors position PLS-SEM as a practical choice.

To infer causality, there has to be an intervention that leads to an outcome in a setting devoid of confounding factors. An observational study cannot accomplish this with regression-based techniques. However, a SCM allows this to be done in observational studies using counterfactual analysis. A counterfactual analysis simulates the presence, absence, or reduction of a treatment variable to evaluate changes in the outcome. This simulated intervention is performed using a machine learning technique. This makes it the perfect tool for asking if a variable is a precursor to another. Also, in an SCM, a DAG could explicitly show OR's placement as an upstream factor, with arrows pointing from OR to each antecedent. The explicit nature of this specification makes it more falsifiable. Within the SCM algorithm, the confounding factors are identified in theory or the literature and incorporated, and this is how they are accounted for.

3.3 Data Collection

3.3.1 Ethics:

The study design was reviewed and approved by the University's Interdisciplinary Committee on Ethics in Human Research. All procedures stipulated within the ethics application were adhered to.

3.3.2 Sample Size

The minimum number of valid participants was determined using the inverse square-root method (Kock & Hadaya, 2018). This method was preferred because it ensures that the relationship between variables in a model is strong enough to be considered statistically significant (Bazan, 2022; Hair et al., 2021). It is expressed in 3.1 where n is the minimum sample size and $|\beta|_{min}$ is the minimum absolute path coefficient between variables.

$$n \geq \left(\frac{z_{.95} + z_{.8}}{|\beta|_{min}}\right)^2 \tag{3.1}$$

From equation 3.1, $z_{.95}$ and $z_{.8}$ represent the 95th percentile (1.645) and 80th percentile (0.8416) of the normal distribution, respectively. Their yields are approximately 2.49 (Kock & Hadaya, 2018):

$$z_{.95} + z_{.8} \approx 2.49 \tag{3.2}$$

For the minimum path coefficient ($|\beta|_{min}$), a value of 0.197 was used. This value is derived from Kock & Hadaya, (2018, p. 20), where it is stated that for "…fairly complex models, as long as they are free of vertical and lateral collinearity …. The corresponding inequality for this proposed rule of thumb would be $\beta/(1 - \beta) > .04$, whose solution is $\beta \geq 197$."

Thus, the minimum sample size required is calculated as

$$n \geq \left(\frac{2.49}{0.197}\right)^2 \tag{3.3}$$

$$n \geq 160$$

Consequently, 160 participants were determined to be sufficient. However, 389 responses were gathered, exceeding this minimum requirement. As a disclaimer, it is important to note that this sample may not fully represent the entire population (Bazan, 2022)

3.3.3 Sampling

A recruitment letter along with study purpose and directions was sent to the students. The Likert scale was adopted, ranging from "1" to "7" (1 indicating disagreement, three indicating ambivalence, and seven indicating agreement). To encourage greater participation, students received a small incentive, including an iPad and $50 gift cards, for completing the survey. Convenience sampling was used to collect data from students at Memorial University of Newfoundland, a public university in Newfoundland and Labrador, Canada. The campaign for data collection was run between June and August 2024.

It is worth mentioning that this study's questionnaires were merged with those from a fellow researcher, who was carrying out a separate study. This is due to significant item overlap between the studies (Dillman et al., 2015). The merging of the items helped to avoid data collection redundancy and reduce participant fatigue. This combined approach also allowed for randomization, concealing the study's primary focus, which can help reduce response biases such as social desirability bias (Tourangeau et al., 2009). A drawback to this method is a lower completion rate: longer surveys may lead to higher levels of incomplete data due to the increased burden on respondents (Rolstad et al., 2011).

3.3.4 Missing data

Data with fewer than four valid rows (approximately 10% per observation) were considered acceptable, accounting for 64% of all responses (Bazan, 2022; Pedersen et al., 2017). The remaining responses were discarded. Following this initial deletion, cells with missing data constituted less than 1% of the entire dataset. Little's test (1988) was then performed to evaluate if the data were missing completely at random. The p-value of Little's test was not statistically significant, indicating a failure to reject the null hypothesis (Little, 1988). If significant, it would have suggested that the data was not missing completely at random. Thus, this would have made it possible to apply imputation techniques to the rows with missing values (Schafer & Graham, 2002). The resulting output of this test is available in Appendix 5. Multiple imputation-chained

Equations (MICE) were used to address missing values, an approach used in machine learning methods (Buuren & Groothuis-Oudshoorn, 2011; Tierney & Cook, 2018). It was deemed suitable due to its ability to handle non-normality and its flexibility in handling different variables. Its ability to refine its imputation on each iteration made it more appealing (Tierney & Cook, 2018). The MICE procedure for python is available in Appendix 4.

3.3.5 Normality

SPSS was used to assess normality. The skewness values for some variables ranged between -1 and 1, with SSN5 showing the highest skewness at 1.076. For kurtosis, OR2 had the lowest value at -1.157. Since these values fall outside the acceptable normality range, they support using PLS-SEM, which accommodates non-normal data (Bazan, 2022; Hair et al., 2021).

3.4 Measures and instrument

This study used a structured questionnaire (see Appendix 1). The validated scale items adapted from the literature to measure each construct. OR was measured using items from Kuckertz et al. (2017). The indicators for ESS used were developed by Trivedi (2016, 2017) and adapted by Bazan et al. (2019). ATB, SSN, PBC, and EI were measured using Liñán and Chen (2009). These shall be described in detail in the succeeding section.

3.4.1 OR:

According to Kuckertz et al. (2017, p.92), "opportunity recognition is characterized by being alert to potential business opportunities, actively searching for them, and gathering information about new ideas on products or services." This definition and its accompanying validated scale were adopted for this study to distinguish opportunity recognition from exploitation. This construct is reflective and has been used extensively in research. Following consultation with peer researchers, minor modifications were made to enhance clarity (see Table 3.1). In addition, its wide and repeated use in the literature (Battour et al., 2022) obviated the need for a pilot study.

Table 3.1 *Modification of the OR scale for this study*

OR	Old Question (Kuckertz et al., 2017)	New Question
OR1	I am always alert to business opportunities	I am very alert to entrepreneurial opportunities.
OR2	I research potential markets to identify business opportunities	I research potential markets to identify entrepreneurial opportunities.
OR3	I search systematically for business opportunities	I actively seek out entrepreneurial opportunities, often employing a systematic approach in my search.
OR4	I look for information about new ideas on products or services	I look for information about new ideas regarding products or services.
OR5	I regularly scan the environment for business opportunities	I regularly scan market trends, customer needs, and competitive landscape to identify potential entrepreneurial opportunities.

3.4.2 ESS:

This construct was adapted from Bazan et al. (2019) and consists of three complementary and mutually dependent measures: entrepreneurial training (ET), entrepreneurial milieu (EM), and start-up support (SS). ET reflects entrepreneurial education's pedagogical and practical aspects, including courses and practical workshops. SS reflects access to funding and mentorship for the students; EM reflects the cultural elements and settings and how they affect entrepreneurship. Each of these measures is a first-order reflective construct.

3.4.3 EI and its antecedents:

The scales for EI and its antecedents were adapted from Bazan (2022), who applied a customized mathematical model to EI based on the work of Liñán & Chen (2009) and Trivedi (2017). These scales form reflective second-order constructs. Notably, SSN, which functions as both an exogenous and endogenous variable, comprises two sets of variables: one reflecting family values and the other reflecting friends' values (Bazan, 2022; Kolvereid, 1996b). These sets were combined as in Bazan (2022).

3.5 Partial Least squares structural equations Modelling

3.5.1 Measurement model analysis

The model under study has nine latent variables in total. Three (ET, EM and SS) form a second-order construct (ESS), while the rest are first-order constructs. The first-order constructs of ET, EM, and SS are all reflective models assigned to ESS via the repeated indicators approach (Bazan 2022). The remaining constructs (OR, ATB, PBC, SSN, and EI) are first-order reflective constructs. Two separate measurement models were thus considered, those for the first and those for the second order, in a holistic manner. In this approach, the first order was linked to the second order (Bazan 2022; Sarstedt et al. 2019). Given that ESS is a second-order reflective construct formed by their respective first-order constructs, the model incorporates reflective measurements at both levels, making it a Type I second-order model (Bazan et al. 2019; Sarstedt, Ringle, and Hair 2022).

3.5.2 Discriminant validity

The Heterotrait-Monotrait (HTMT) ratio and the *Fornell-Larcker criterion* are indices used to assess discriminant validity. They are displayed in Tables 3.2 and 3.3, respectively. They ensure that constructs within a model are distinct and measure unique concepts (Henseler et al., 2015). Discriminant validity reduces potential overlap between constructs, essential for accurate model assessment. The HTMT ratio is calculated by dividing the average of between-trait correlations (heterotrait-heteromethod) by the average of within-trait correlations (monotrait-heteromethod).

Generally, an HTMT value below 0.85 is considered a strict threshold, while values up to 0.90 may be acceptable in specific research contexts (Henseler et al., 2015).

$$HTMT_{ij} = \frac{avg.\ between - trait\ correlations}{avg.\ within - trait\ correlations} \tag{3.4}$$

According to the Fornell-Larcker criterion, for each construct, the root of its Average Variance Extracted (AVE) has to exceed the absolute value of its correlation with any other construct within the model. It is expressed in Equation 3.5, where AVE_i is the average variance extracted of construct, i and r_{ij} is the correlation between constructs i and j. (Ab Hamid et al., 2017; Fornell & Larcker, 1981):

$$\sqrt{AVE_i} > |r_{ij}| \tag{3.5}$$

The HTMT ratio revealed acceptable discriminant validity within the model, except between ATB and EI, which showed an HTMT value of 0.926 — exceeding the established threshold of 0.85. The Fornell-Larcker criterion was also applied. The square root of the AVE for ATB equalled its correlation with EI, indicating potential issues with discriminant validity (Fornell & Larcker, 1981). Correlations in the outer model for the residuals between these variables were analyzed to address this. The highest observed correlation was 0.255 - indicating a relatively low association. Subsequently, cross-loadings were examined, revealing that each indicator loaded more strongly on its designated construct than on any other construct, supporting discriminant validity (Hair et al., 2019). To improve discriminant validity, ATB2, ATB4, and EI2 were removed based on item redundancy. Specifically, ATB2 ("I would prefer to run my own business than work for someone else") appeared redundant when compared to ATB4 ("Among various career options, I would rather be an entrepreneur"), as both reflected a preference for entrepreneurship over traditional employment.

Similarly, EI2 was removed because it indicates a strong commitment to entrepreneurship as a career path, which overlappes with ATB1 and ATB4. After removing these items, the HTMT value between ATB and EI was reduced to 0.888, and the Fornell-Larcker matrix showed improved discriminant validity, with diagonal values higher than other values in their rows and columns. Although 0.888 slightly exceeds the preferred threshold (Hair et al., 2019), it remains below 0.9, another acceptable threshold in the literature (Henseler et al., 2015).

3.5.3 Indicator reliability

All outer loadings were greater than 0.6 which indicates a statistically significant relationship (Hair et al., 2019; Yana et al., 2015). Consequently, all constructs are deemed reliable.

3.5.4 Internal consistency

Cronbach's alpha, a measure of internal consistency, evaluates the relatedness of a set of items within a group (see Table 3.5). It expresses whether items measuring the same construct yield similar scores, and its acceptable threshold is 0.7 (Bazan et al., 2022; Tavakol & Dennick, 2011). It is expressed in Equation 3.6, where $\sigma^2{}_i$ represents the variance of the item i; $\sigma^2{}_t$ denotes the variance of the total score obtained by summing all the items; k is the number of items (Tavakol & Dennick, 2011).

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma^2{}_i}{\sigma^2{}_t}\right) \tag{3.6}$$

Composite reliability assesses how well a set of items reflects their underlying latent variable (see Table 3.5). It considers each indicator's factor loading and generally provides a more accurate measure than Cronbach's alpha (Bagozzi & Yi, 1988). It is expressed in Equation 3.7 where λ_i

represents the standardized loading of item i, while θ_i denotes the measurement error variance for item i (Bazan et al., 2022; Bagozzi & Yi, 1988):

$$CR = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k} \theta_i} \tag{3.7}$$

High internal consistency typically indicates that these measures can be reproduced under stable conditions (Hair et al., 2019; Nunnally & Bernstein, 20). Both Cronbach's Alpha and composite reliability for all measures were above 0.70, indicating satisfactory reliability (Hair et al., 2019).

3.5.5 Convergent reliability

Convergent reliability is the degree to which multiple items intended to be designed for the same construct consistently represent that underlying variable. It ensures that items designed for a construct are reflective of it. The average variance extracted (AVE) is used to evaluate this index (see Table 3.5). The AVE captures the proportion of variance in a construct that is explained by the items relative to variance attributed to measurement error. It is calculated as the mean of the square loadings of the items on their respective latent variables (Hair et al., 2019, 2021a). It is expressed in equation 3.8, where *n* is the number of items and λ_i is the standardized factor loading on item i.

$$AVE = \frac{\sum {\lambda_i}^2}{n} \tag{3.8}$$

The acceptable threshold for this measure is 0.5, indicating that the construct is capable of capturing 50% or more of the variance in the construct (Bazan et al., 2022; Hair et al., 2019). The Average Variance Extracted (AVE) in all constructs surpassed the 0.50 benchmark (Hair et al., 2019), with the SSN construct displaying the lowest AVE at 0.555.

3.6 Structural model analysis

In this analysis, the structural model measures how the constructs relate to one another.

3.6.1 Collinearity

The variance inflation factor (VIF) is the index used to detect multi-collinearity in a regression analysis (see Table 3.6). Multi-collinearity occurs when two or more correlated independent variables are capable of causing issues in estimating the model coefficient, which is why this index is important (Bazan et al., 2022; Hair et al., 2019). It is expressed in Equation 3.9 where, R^2 represents the coefficient of determination obtained by regressing the independent variable on all other predictors in the model:

$$VIF = \frac{1}{1 - R^2} \tag{3.9}$$

A VIF of 3.3 or higher for any variable in the inner model suggests the presence of common method bias (Kock, 2015). In this study, the highest VIF observed was 1.766 in the relationship between PBC and EI, as shown in Table 3.7, which is well within acceptable thresholds.

3.6.2 Common Method bias:

Bearing in mind that all VIF values are within threshold limits, one could argue that the study is free from common method bias (Kock et al., 2012). However, this does not rule out the potential presence of this bias. This is because self-reported measures could correlate due to social desirability and consistency motives.

3.6.3 Coefficient of determination

The coefficient of determination is the extent to which independent variables account for the entire variance in the dependent variable. A higher value implies the model's effectiveness in describing the relationship between variables. It could also be used in evaluating model fit and as a criterion in comparing different models to explain which represents the data. They can be measured through the coefficient of determination *(R^2)*. As stated earlier, this is given by:

$$R^2 = 1 - \frac{SS_{residuals}}{SS_{total}} \tag{3.10}$$

$$R^2 = \frac{SS_{regression}}{SS_{total}}$$

From the above, SS indicates sums of squares (Dombrowsky, 2023; Gelman, 2005; Su et al., 2012; Tranmer & Elliot, 2008). The variables with the highest R^2 were EI and PBC, which gave 0.771 and 0.558, respectively — considered to be strong in the literature (Bazan et al., 2022; Hair et al., 2011; Rigdon, 2012). ATB and SSN followed this, giving moderate values of 0.430 and 0.273, respectively. The weakest was OR, which gave a value of 0.167.

3.6.4 Effect size

It is used to evaluate the change in R^2 of an endogenous variable when one of its predictors is eliminated (Bazan et al., 2022). It is denoted as f^2, and can be used to express the extent of mediation – whether full or partial (Nitzl, 2016; Bazan et al., 2022). It is expressed as(Bazan, 2022; J. Cohen, 1992, 2013; Sarstedt et al., 2022):

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}} \tag{3.11}$$

From the above, $R^2_{included}$ is the R^2 used when predictors in context are included in the model, while $R^2_{excluded}$ is that used when predictors are excluded. Cohen's (1992, 2013) threshold for effect size is specified as 0.02, 0.15, and 0.35 for small, medium, and large effect sizes, respectively. Following this, it can be seen that the removal of ESS had a moderate effect on OR (0.118); the removal of OR, on the other hand, had a substantial effect on ATB (0.416), PBC (0.657) and a moderate effect on SSN (0.316) (Cohen, 2013). Regarding the removal of EI antecedents, PBC and ATB had a large effect on EI (0.423 and 0.865, respectively); SSN, on the other hand, has a negligible impact on EI at 0.000.

3.6.5 Predictive relevance

This is an index of the predictive accuracy of a model (Geisser, 1975; Stone, 1974). It is also known as the Stone-Geisser Q^2. As recommended, if this value is greater than 0.00, it is small; if greater than 0.25, it is moderate; if greater than 0.5, it is substantial. However, values less than 0 reflect poor model prediction. The Q^2 of all endogenous variables was greater than 0, indicating predictive relevance. However, regarding the degree of relevance, they were all small because none were up to 0.25., with the largest being OR (0.153) and the smallest being EI at 0.05.

3.6.6 Hypothesis testing:

Bootstrapping with 5000 subsamples was run for the parameters to test the hypothesis by analyzing direct effects.

*Direct effect*s

The analysis of the direct relationship between the model's constructs reveals several significant relationships, supporting most of the hypotheses (see Table 3.7). The relationship between ESS and OR is positive. All hypotheses regarding the relationship between OR and the antecedents of EI ($p < 0.01$) are supported. All except SSN are statistically significant regarding the relationship between Ajzen's antecedents and EI. ATB and PBC are shown to have a statistically significant effect on EI. Regarding the relationship between EI and SSN, it gave a p-value of 0.848, which is not statistically significant. Following Kolvereid (1996b), the effect of SSN on the other antecedents is observed in that both ATB and PBC gave a statistically significant relationship.

Thus, all hypotheses are confirmed from H1-H9 except H8. Their confidence intervals are revealed in Table 3.7.

3.6.7 Moderation

In this study, men were coded one, and women were coded two. Only the relationship between ESS and OR was significantly negatively moderated by gender. This moderation could mean that the relationship between OR and ESS will show greater significance in men compared to women. Upon carrying out a slope analysis, the relationship between OR and SSN might not have shown statistical significance; however, it was shown to be non-parallel, unlike those regarding the relationship between OR and Ajzen's antecedents.

3.5.8 Correlation

Some high correlations were observed among certain constructs (see Table 3.4). EI correlated highly with ATB, PBC and OR (0.812, 0.752 and 0.771 respectively). These relationships align with the theory of planned behavior and other empirical findings. In addition to its correlation with EI, OR showed high correlation with PBC (0.726) and moderate correlation with SSN and ATB (0.501 and 0.640 respectively).

Table 3.2 *Heterotrait Monotrait Ratio*

	ATB	**EI**	**ESS**	**Gender**	**OR**	**PBC**	**SSN**	**Gender ∗ OR**	**Gender ∗ ESS**
ATB									
EI	0.888								
ESS	0.167	0.225							
Gender	0.070	0.093	0.161						
OR	0.707	0.832	0.394	0.141					
PBC	0.660	0.819	0.352	0.152	0.799				
SSN	0.533	0.554	0.424	0.223	0.595	0.631			
Gender∗OR	0.032	0.061	0.197	0.318	0.052	0.061	0.162		
Gender∗ESS	0.132	0.151	0.044	0.275	0.187	0.112	0.039	0.094	

Table 3.3 Fornell Larcker Criterion

	ATB	EI	ESS	Gender	OR	PBC	SSN
ATB	0.908						
EI	0.812	0.914					
ESS	0.153	0.211	0.939				
Gender	0.067	0.089	0.156	1.000			
OR	0.640	0.771	0.367	0.135	0.858		
PBC	0.594	0.752	0.318	0.144	0.726	0.825	
SSN	0.439	0.467	0.347	0.194	0.501	0.516	0.800

Table 3.4 Correlation

	ATB	EI	ESS	Gender	OR	PBC	SSN	Gender x OR	Gender x ESS
ATB	1.000								
EI	0.812	1.000							
ESS	0.153	0.211	1.000						
Gender	0.067	0.089	0.156	1.000					
OR	0.640	0.771	0.367	0.135	1.000				
PBC	0.594	0.752	0.318	0.144	0.726	1.000			
SSN	0.439	0.467	0.347	0.194	0.501	0.516	1.000		
Gender∗OR	-0.030	-0.059	-0.190	-0.318	-0.044	-0.055	-0.132	1.000	
Gender∗ESS	-0.124	-0.146	-0.043	0.275	-0.178	-0.107	0.017	-0.094	1.000

Table 3.5 Factor indicator loadings

		Indicator loadings	Indicator reliability	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted (AVE)
ATB	**ATB1**	0.934	0.872	0.893	0.897	0.933	0.824
	ATB3	0.918	0.843				
	ATB5	0.870	0.757				
EI	**EI1**	0.854	0.729	0.934	0.934	0.953	0.835
	EI3	0.925	0.856				
	EI4	0.937	0.878				
	EI5	0.937	0.878				
OR	**OR1**	0.875	0.766	0.91	0.916	0.933	0.736
	OR2	0.900	0.810				
	OR3	0.859	0.738				
	OR4	0.763	0.582				
	OR5	0.885	0.783				
PBC	**PBC1**	0.841	0.707	0.883	0.889	0.914	0.681
	PBC2	0.812	0.659				

	PBC3	0.850	0.722				
	PBC4	0.791	0.626				
	PBC5	0.830	0.689				
SSN	**SSN15**	0.890	0.792	0.72	0.761	0.84	0.64
	SSN26	0.818	0.669				
	SSN35	0.677	0.458				
ESS	**ET**	0.936	0.876	0.933	0.942	0.957	0.881
	SS	0.944	0.891				
	EM	0.936	0.876				

Table 3.6 *Variance Inflation Factor (VIF)*

ATB → EI	**ESS → ATB**	**ESS → EI**	**ESS → OR**	**ESS → PBC**	**OR → ATB**	**OR → EI**	**OR → PBC**	**OR → SSN**	**PBC → EI**	**SSN → ATB**	**SSN → EI**	**SSN → PBC**
2.04	1.12	1.20	1.00	1.12	1.35	2.34	1.35	1.00	2.35	1.33	1.61	1.33

Table 3.7 *Total Direct Effects*

	Path coefficients	**Sample mean (M)**	**Standard deviation (STDEV)**	**T-value**	**P-value**	**Confidence intervals [2.5%, 97.5%]**	
ATB → EI	0.564	0.564	0.031	18.181	0.000	0.504	0.623
ESS → OR	0.337	0.340	0.046	7.281	0.000	0.248	0.429
Gender→ATB	-0.040	-0.039	0.043	0.922	0.356	-0.121	0.047
Gender→ OR	0.138	0.140	0.045	3.098	0.002	0.054	0.227
Gender→PBC	0.023	0.022	0.039	0.591	0.555	-0.055	0.097
Gender→SSN	0.104	0.104	0.044	2.367	0.018	0.018	0.193
OR→ATB	0.563	0.563	0.041	13.655	0.000	0.479	0.640
OR → PBC	0.623	0.623	0.041	15.198	0.000	0.539	0.699
OR → SSN	0.484	0.488	0.041	11.680	0.000	0.405	0.567
PBC→EI	0.413	0.413	0.036	11.383	0.000	0.340	0.484
SSN→ATB	0.165	0.166	0.042	3.910	0.000	0.083	0.249
SSN→EI	0.006	0.006	0.030	0.192	0.848	-0.054	0.065
SSN→PBC	0.199	0.202	0.044	4.548	0.000	0.118	0.290
Gender∗OR→ATB	0.004	0.003	0.051	0.083	0.934	-0.099	0.105
Gender∗OR→ PBC	0.006	0.004	0.041	0.154	0.878	-0.081	0.082
Gender∗OR→ SSN	-0.085	-0.078	0.060	1.416	0.157	-0.188	0.043
Gender∗ESS→OR	-0.206	-0.199	0.058	3.546	0.000	-0.299	-0.069

3.7 Monte Carlo Simulation

Monte Carlo Simulation s a computational tool that generates data and uses it to analyze the variability and robustness of statistical models (Schamberger, 2023). It uses repeated random sampling in generating numerical outputs, particularly for complex or infeasible models. The method relies on the randomness in sampling to assign uncertain parameters to variables based on predefined distributions. The model is run repeatedly using randomly generated input combinations - which makes it an iterative process. These randomly generated inputs ultimately result in a distribution of outcomes that could be used to make statistical inferences. It ensures reliable estimates with sufficient iterations by exploiting the law of large numbers. Within the context of SEM, the Monte Carlo simulation helps to evaluate the effect of sample size on a model, the performance of model fit indices, and the behaviour of path coefficients under different conditions. The procedure for this simulation in this study follows those outlined in Schamberger (2023), who uses a data-generation process specifically geared toward variance-based methods like PLS-SEM.

In this study, the aim of the simulation is to explore the effect of sample size on the generated model and to assess different estimation methods. At n=160, all path coefficients were significant. However, at n=500, all but the SSN-to-EI path coefficient remained significant. The proportion of admissible results was ~37% at n=160 and increased to ~86% at n=500. From the ratio of significant path coefficients, it could be inferred that the model is stable regardless of sample size. It could also be inferred that the model is more representative of the underlying population with an increased sample size. The image output is available in Appendix F.

3.8 ESS as a Covariate:

According to the literature, ESS directly effects ATB, SSN and PBC (Trivedi 2016 & 2017; Bazan et al., 2019; Bazan, 2022). Thus, ESS is considered a covariate in this study because, from the literature, it affects both OR and the antecedents of EI.

3.9 Causal Analysis

After the direct effects were carried out using PLS-SEM, the latent variable scores were extracted for the causal analysis (Richter & Tudoran, 2024). In this analysis, the main focus was on OR as a precursor to the antecedents of EI. That is, the causal effect of OR on ESS, ATB, and PBC was tested with ESS as the sole covariate. The workflow for a causal analysis is very straightforward. It involves specification, identification, estimation, and refutation. Regarding the do-why implementation in python this paper followed instructions detailed in Sharma and Kiciman (2020). The code is available in Appendix 3.

3.9.1 Specification:

The specification process follows the model development for a structural equation. This has already been implemented in the PLS-SEM stage (with the exception of the gender moderation phase which was not the focus of this stage).

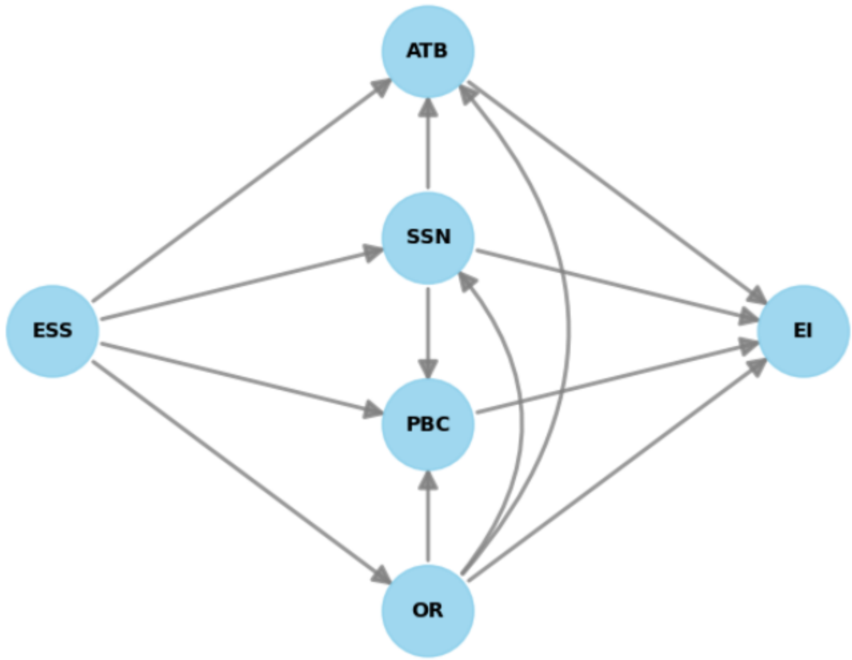

Figure 2 Directed acyclic graph of causal model

3.9.2 Identification:

In this step, do-calculus (Pearl, 1998, 2010), is performed to transform expressions involving interventions into expressions involving only observational data given a causal graph (See Appendix 2). Regarding the identification, the full technical details are discussed in Neal (2020) and Pearl (1998, 2010, 2012). The image output is available in the appendix section.

Interpretation:

This criterion involves finding a mediator that the treatment effect influences which in turn affects the outcome. The absence of such variable s means that the front-door identification could not be applied in this analysis. Based on the identification strategy, the backdoor criterion was used to estimate the average treatment effect. This involves conditioning on the covariate ESS to satisfy the confoundedness assumption. The same procedure and steps were carried out for SSN and ATB, with the same results: no front door or suitable instrumental variable was identified. Their output images are attached below. Their only backdoor estimand was ESS.

3.9.3 Estimation

To get the effect of a treatment variable on a dependent or outcome, this is usually expressed as an estimation of the difference between a treatment and a control (no treatment). A control is generally as $\mathrm{do}(\mathrm{A} = 0)$. Therefore, an estimation could be expressed as difference between an intervention and a control. This is expressed in Equation 3.11. It is known as the causal effect difference (Pearl, 1998, 2010; Pearl et al., 2016).

$$P\big(B = 1 \big| do(A = 1)\big) - P\big(B = 1 \big| do(A = 0)\big) \tag{3.11}$$

In implementing the operation in Equation 3.11, the dependency, B has on any variable is severed, and thus eliminating any confounder in the effect between A and B. Bearing in mind that this is not computed for each variable but averaged over the entire dataset. The average treatment effect could be expressed in Equation 3.12 as

$$E[Y \mid do\ (T = 1)] - E[Y \mid do(T = 0)] \tag{3.12}$$

Normally, this would have been expressed as in Equation 3.13

$$E[Y(1)] - E[Y(0)] \tag{3.13}$$

However, Equation 3.12 is easier to estimate. In addition, it is more robust to missing data. This is because it only deals with observed datapoints, via randomized trials (Wager, 2020). For a non-parametric reduction problem, given:

$$\mu_{(\mathrm{t})}(\mathrm{x_i}) = \mathrm{E}[\mathrm{Y_i} \mid \mathrm{X} = \mathrm{x}, \mathrm{T} = \mathrm{t}] \tag{3.14}$$

The average treatment effect could be expressed as in Equation 3.15 where $\mu_{(\mathrm{t})}(x_I)$ is the solution to a non-parametric regression problem (Wager, 2020).

$$\mathrm{E}[\mu_{(1)}(\mathrm{X_i}) - \mu_{(0)}(\mathrm{X_i})] \tag{3.15}$$

The estimation results reveal that OR significantly influences ATB, PBC, and SSN (see Table 3.8). Specifically, increasing OR from 0 to 1 raises PBC by 0.704, ATB by 0.675, and SSN by 0.432, with all effects being highly significant ($p < 0.001$) across the dataset representing the data distribution/population. The program output is available in the appendix section.

Table 3.8 *Causal inference of OR on EI Antecedents*

	Mean	**P-value**	**Confidence intervals [Lower, Upper]**	
OR → PBC	0.704	3.15e-56	0.630	0.778
OR → ATB	0.675	3.39e-45	0.248	0.429
OR→SSN	0.432	9.65e-19	0.593	0.758

3.9.4 Refutation:

Refutations, in this context, are used to test the robustness and validity of causal conclusions(Pearl, 1998; Pearl et al., 2016). They help assess whether the identified causal effect is sensitive to potential violations of assumptions or the presence of confounding factors (Pearl et al., 2016). One common refutation method is the placebo test. Its main objective is to ascertain if a placebo variable (Z), which is not supposed to incur a causal effect on the outcome(Y), shows a significant effect. This would indicate potential confounding or model misspecification.

The hypothesis test works as follows (Pearl et al., 2016):

Null hypothesis (H_0):

$$\beta_z = 0$$

Alternate (H_1):

$$\beta_z \neq 0$$

Given the linear model in Equation 3.16, where A is the treatment and X is the covariate and ε is the error term:

$$Y = \beta_0 + \beta_A A + \beta_X X + \varepsilon \quad (3.16)$$

The model is extended such that a Covariate (Z) is chosen, and assumed to have no causal effect on Y.

$$Y = \beta_0 + \beta_A A + \beta_X X + \beta_z Z + \varepsilon \quad (3.17)$$

If a standard regression is carried out and β_z is not zero, it means that the model above is wrong, else, it means the model is robust (Pearl et al., 2016).

From Table 3.9, it can be seen that using a placebo as a treatment: if this treatment moves from 0 to 1, it will only affect PBC by -0.00197; ATB by -0.00149; SSN by 0.006, which represents a -370, -453.02, and 72.79 change in the magnitude of effect, respectively. It is worth noting that a permute placebo type was used, meaning that the treatment variable is permuted randomly across datasets and will result in a new effect estimate every time. However, despite this permutation, the placebo treatment will remain magnitudes lower than the treatment effect (Imbens, 2000).

Table 3.9 *Refutation of the causal model*

Causal Relationship	Estimated causal effect	Placebo Causal Effect	P-value (Placebo)	Absolute Magnitude change
OR → PBC	0.704	-0.0020	0.94	370.00
OR → ATB	0.675	-0.0015	0.96	453.02
OR→SSN	0.432	0.0060	1.00	72.790

3.9.5 Sensitivity analysis:

Sensitivity analysis in causal models assesses how robust the results are to potential unmeasured confounding or violations of model assumptions. In causal inference, sensitivity analysis helps determine whether the estimated causal effect remains consistent under different levels or forms of bias, providing insight into how much an unmeasured confounder would need to influence the results to change the conclusions. It could involve testing the stability of causal effects by varying model parameters. It could also achieve this by simulating the impact of hypothetical confounders. This approach is particularly valuable in observational studies, where unmeasured confounding is a primary concern. Rosenbaum and Rubin (1983) introduced frameworks for sensitivity analysis to assess treatment effects, while VanderWeele (2015) provided a comprehensive treatment of methods for sensitivity analysis in causal inference.

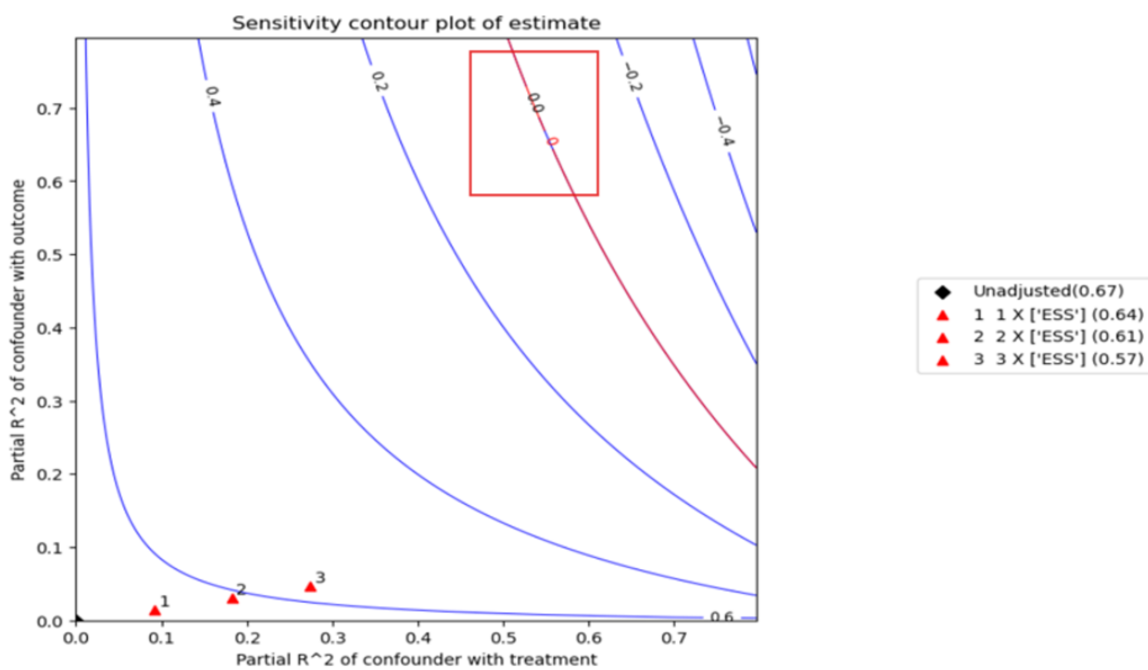

Figure 3 Contour plot using PBC as outcome variable

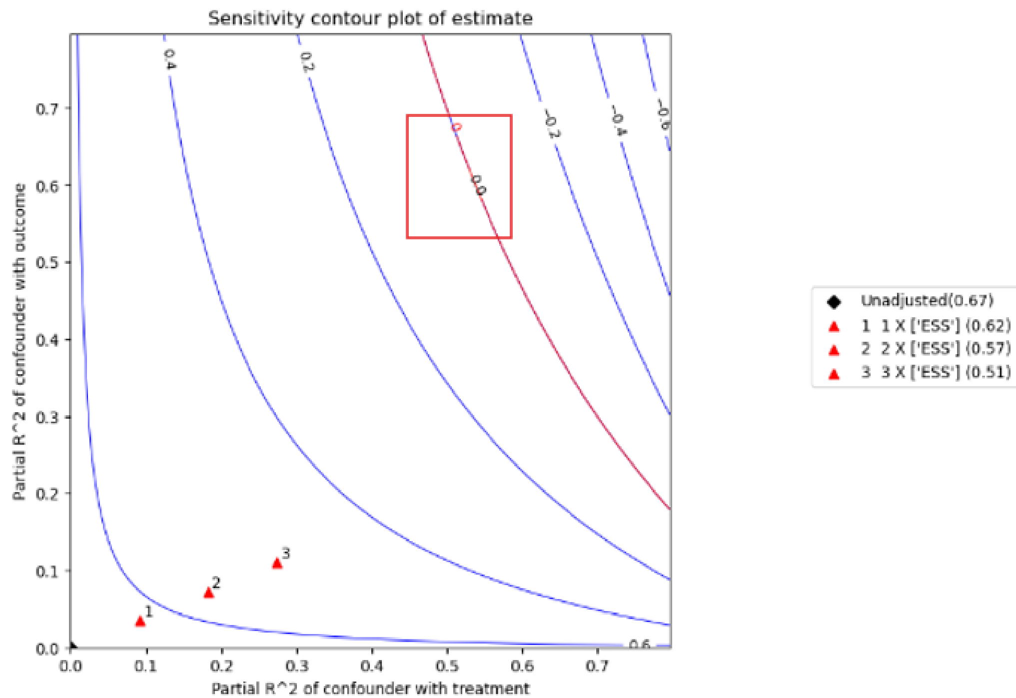

Figure 4: Contour plot using ATB as outcome variable

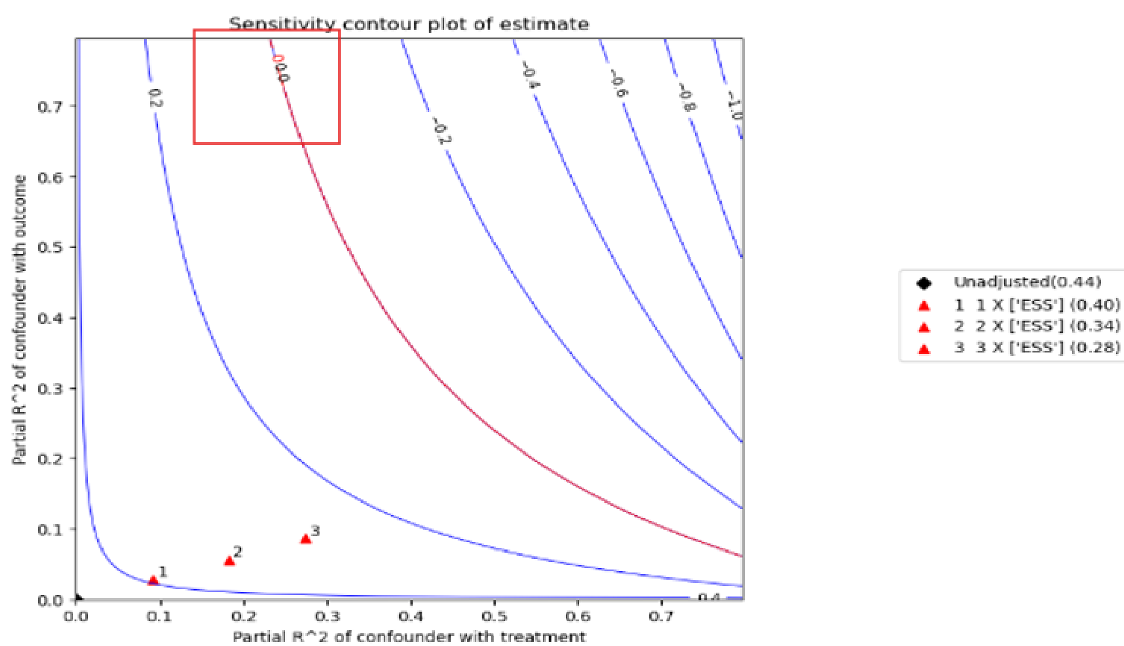

Figure 5: Contour plot using SSN as outcome variable

The above can be interpreted thus: If the red triangles are close to or on the 0.0 contour line, the estimated effect is likely not sensitive to unmeasured confounding with the specified. If it passes the 0.0 contour and moves more rightward, the sign will flip, and the opposite effect will be experienced in the presence of an unobserved confounder. Therefore, points that are further away from the origin on the X and Y axis indicate scenarios where unmeasured confounders could have a larger impact on the estimate(Cinelli & Hazlett, 2020). Therefore, the above indicates that our model is robust to unobserved covariates. Note that the square outline in the graph screenshot was added by the researcher to prevent confusion when converting the image to black and white.

Chapter 4 Discussion

The goal of any scientific study is to get to the underlying truth, regardless of the methodology. Correlations evaluate relationships in observational studies. However, randomized control experiments assess cause and effect in interventional studies - this is the gold standard (Song, 2014; López De Prado, 2023). These randomized control experiments are not always feasible. This is because controlled observations can be time-consuming, and the exact timing of the cause might not be controllable (López De Prado, 2023). Therefore, causal inference comes in as a hybrid between these. They can evaluate cause and effect by simulating interventions in observational studies. While simulated interventions using causal inference cannot replace randomized control trials, they add some rigor and account for misleading correlations (López De Prado, 2023). They also provide a basis for a randomized control experiment. Furthermore, they are more open to refutation, which is one reason for their appeal to researchers (López De Prado, 2023).

The PLS-SEM analysis revealed a positive relationship between the ESS and OR, consistent with the Austrian perspective on OR (Davidsson & Honig, 2003; Shane, 2000). From this perspective, it can be understood that ESS provides a unique knowledge stock via information asymmetry (Baron, 2006). This unique knowledge stock is pivotal in students' ability to identify entrepreneurial opportunities oblivious to others. A potential insight here could be directed toward educational policy. In alignment with Baron (2006), proficiency in OR can be enhanced through education focused on pattern recognition.

The structural equations and causal models show that OR positively affects the EI antecedents. The Austrian theory of entrepreneurial opportunity explains the effect of OR on ATB and PBC. The effect of OR on SSN could be explained by Schneider's attraction-selection attrition framework (Schneider et al., 1995). Following the Austrian perspective, information asymmetry enhances students' self-efficacy (Ferreira-Neto et al., 2023; Mukhtar et al., 2021). Once these students recognize opportunities, their feasibility and appeal towards entrepreneurship will be bolstered. In line with the attraction-selection attrition framework, recognizing opportunities motivates students to seek out people and environments that support and encourage pursuing these opportunities (Schneider, 1987; Tom, 1971; Vroom, 1966). Thus, in line with the findings and the theoretical insights, opportunity recognition could be positioned as a precursor to the antecedents of entrepreneurial intention. The argument that recognizing opportunities precedes the development of an entrepreneurial mindset is thus reinforced (Krueger, 2000).

Other measured variables, which could serve as confounders, were post-treatment covariates. Controlling every possible confounder is impossible, and some scientists include as many control variables as possible to block confounders. This is often cautioned against because it risks introducing some biases (López De Prado, 2023). For example, controlling for these post-treatment variables could introduce collider bias, leading to false associations (López De Prado, 2023; Pearl, 2010). ESS was the only covariate controlled for because, from the literature, it was the only pre-treatment factor that could also affect the outcome (Bazan, 2022; Liao et al., 2023; St-Jean et al., 2017).

In examining the interrelationships within Ajzen's (1991) framework, it was observed that, apart from SSN, none of the antecedents showed a positive relationship with EI. This was an equal observation in Bazan (2022). The inconsistency in the SSN-EI link highlights the need to reconsider the theoretical connection between SSN and EI.

Additionally, there was gender moderation between ESS and OR. Men exhibited a more significant relationship than women in this link. Gender role theory might offer some explanation for this. Based on this theory, men may be more conditioned to see the potential in entrepreneurial opportunities, while women might be more attuned to assessing risk (Eagly & Wood, 2012; Tsai et al., 2016b). Another is aligned with gender schema theory. From this theory, it could be gendered experiences within the might shape perceptions of social support within the institution (Bem, 1981; Emami et al., 2023). A possible policy implication is that targeted educational programs could be developed to address gender-specific challenges in using education to recognize entrepreneurial opportunities.

The findings did not support the hypothesis that gender moderates the relationship between opportunity recognition and the antecedents of entrepreneurial intention. One possible explanation is equal access to resources and education - within the university. Both genders have comparable access to resources and education to foster opportunity recognition. Another possible reason could be that in Atlantic Canada, gender roles are less differentiated. This reduced differentiation dampens the moderation effect of gender between these variables. This lack of gender moderation hints that initiatives that foster entrepreneurial intention through opportunity recognition may be effective across genders.

Chapter 5 Conclusion and Recommendation

5.1 Conclusion

It could be concluded from the regression analysis that ESS directly affects OR. From the OR regression and causal analysis, it could be concluded that OR has a relationship with and causal effect on the antecedents of EI. From the regression analysis, it could be concluded that gender moderates the relationship between ESS and OR. However, it does not moderate the relationship between OR and the antecedents of EI. From this, there is still work to be done to understand why women are less likely than men to pursue entrepreneurship despite recognizing opportunities. However, it does raise questions about whether gender differences in the relationship between ESS and OR could help explain this.

From a methodological perspective, no paper in business research has combined PLS-SEM and SCM methodologies using extracted latent variable scores (Richter and Tudoran, 2024). This study highlights the suitability and possible insight of these combined methods.

5.2 Limitation

- The participants' statements regarding their OR, EI, ATB, PBC, and SSN were taken to be reliable. There is no other way of measuring these variables (Datta et al., 2022).
- The finding within this study is context specific. The results may vary based on the environment of the participants.
- A convenience sampling was used. Only students within memorial university were contacted. Thus, it is not representative of the entire population.

- There is also a possibility of reverse causality, where EI antecedents may influence OR rather than the assumed direction. While theoretical justification and model specification support the proposed causal structure, future research could explore longitudinal designs or instrumental variable approaches to further address this concern.
- This study uses cross-sectional data, which limits causal inference. Cross-sectional data pose challenges since counterfactuals often rely on assumptions about latent dynamics or unobserved variables that evolve over time. While SCMs can generate counterfactuals in a static cross-sectional setting, the lack of temporal data can limit their validity compared to longitudinal studies. Future research using longitudinal or experimental data is needed to establish causality with greater confidence.

5.3 Recommendation

- Heterogeneous Treatment Effect: To further understand the causal relationship between ESS, OR, EI, and its antecedents, it would be useful to explore the heterogeneous treatment effects in their relationships. Advanced algorithms like the X-learner offer opportunities for novel approaches in this area (Künzel et al., 2019).
- Covariates: Literature has to be examined for other covariates besides ESS in the relationship between OR and Ajzen's antecedents. For example, self-efficacy was observed to affect both OR and PBC. However, it was not measured in this study (Tominc & Rebernik, 2007; Nicolaou & Shane, 2010; Garg et al. 2011).
- A randomized control experiment: To corroborate the findings in this study, a randomized control experiment could be conducted. This test should use OR as an intervention and EI antecedents as outcome variables.

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Appendix

Appendix 1: Questionnaire Items

You have the option to skip any question you prefer not to answer.

Please indicate your level of agreement with the below statements based on the following scale:

1. I completely disagree
2. I disagree
3. I rather disagree
4. I neither agree nor disagree
5. I rather agree
6. I agree
7. I completely agree

In addition, If you complete the survey but decide that you do not want to submit it, you can press the 'Do Not Submit' button, and the system will redirect you to the email intake form for the draw without recording or submitting your response.

Opportunity Recognition (OR)

- OR1 — I am very alert to entrepreneurial opportunities.
- OR2 — I research potential markets to identify entrepreneurial opportunities.
- OR3 — I actively seek out entrepreneurial opportunities, often employing a systematic approach in my search.
- OR4 — I look for information about new ideas ~~on~~ regarding products or services.
- OR5 —I regularly scan market trends, customer needs, and competitive landscape to identify potential entrepreneurial opportunities.
- OR6 - How many entrepreneurial opportunities have you identified since you commenced your studies at Memorial University?
  <dropdown>

Attitude Towards Behavior (ATB)

- ATB1—A career as an entrepreneur is attractive to me.
- ATB2—I would prefer to run my own business than work for someone else.
- ATB3—Being an entrepreneur would give me great satisfaction.
- ATB4—Among various career options, I would rather be an entrepreneur.

- ATB5—If I had the opportunity and resources, I would like to start a business.

Subjective Social Norms (SSN)

- SSN1—My immediate family values the entrepreneurial career more than any other careers
- SSN2—My friends value the entrepreneurial career more than any other careers.
- SSN3—My immediate family would approve of my decision to start a business.
- SSN4—My friends would approve of my decision to start a business.
- SSN5—The expectations of my immediate family are important to me.
- SSN6—The expectations of my friends are important to me.

Perceived Behavioral Control (PBC)

- PBC1—I am prepared to start a viable business.
- PBC2—If I wanted to, I could easily pursue a career as an entrepreneur.
- PBC3—Starting a business and keeping it viable would be easy for me.
- PBC4—I know the necessary practical details to start a business.
- PBC5—If I tried to start a business, I would have a high probability of success.

Entrepreneurial Intention (EI)

- EI1—I am ready to do what it takes to be an entrepreneur.
- EI2—My professional goal is to be an entrepreneur.
- EI3—I will make every effort to start and run my own business.
- EI4—I am determined to start my business in the future.
- EI5—I am seriously thinking about starting my own business.

University Environment & Support System (ESS)

- SS1—Memorial University organizes business idea competitions.
- SS2—Memorial University has many resources to support a start-up company.
- SS3—Memorial University provides students with ideas to start a new business.
- SS4—Memorial University arranges meetings with successful entrepreneurs to share their experiences.
- SS5—Memorial University provides students with the financial means needed to start a new business.
- ET1—Memorial University provides students with the knowledge needed to start a new business.
- ET2—Memorial University offers training in entrepreneurship.
- ET3—Memorial University arranges conferences and workshops on entrepreneurship.
- ET4—Memorial University arranges for mentoring and advisory services for student entrepreneurs.
- ET5—Memorial University offers to work in projects that focus on entrepreneurship.
- EM1—Memorial University provides a creative atmosphere to develop ideas for new business start-ups.

- EM2—Memorial University helps students build the required network for starting a business.
- EM3—Memorial University motivates students to start a new business.
- EM4—Memorial University creates awareness of entrepreneurship as a possible career choice.
- EM5—Memorial University brings entrepreneurial students in contact with each other.
- ESS0 – Memorial University is an entrepreneurial university.

Demographics

If I were to start a business, it would be a <dropdown for type of business>

My age is: <dropdown> (+Prefer not to say)

I am a(n) ☐ student from Newfoundland & Labrador ☐ student from another Canadian province ☐ international student ☐ Prefer not to say

I am a(n) ☐ undergraduate ☐ graduate student ☐ Prefer not to say

I identify as a: ☐ male ☐ female ☐ Other (Please specify) ☐ Prefer not to say

My area ~~if~~ of study is: <dropdown> ☐ Prefer not to say

Faculty/School <dropdown> ☐ Prefer not to say

This is my ☐ first ☐ second ☐ third ☐ fourth ☐ fifth ☐ sixth year in my program ☐ Prefer not to say.

I identify as ☐ Indigenous ☐ a member of a visible minority ☐ None of the above

☐ Prefer not to say

Do not submit☐ (By pressing this button, the system will redirect you to the email intake form for the draw without recording or submitting your response)

Appendix 2: Front door and Back Door Proofs for Identification

Here, do-calculus (Pearl, 1998, 2010), is performed to transform expressions involving interventions into expressions involving only observational data given a causal graph.

The rules of do-calculus are expressed below See (Neal, 2020; Pearl, 1995):

Rule 1 (Insertion/Deletion of Observations):

$$P(Y|\ do(A), B, C) = P(Y \mid do(A), C)$$

if Y $\coprod$ $B \mid A, C$, in the graph where incoming arrows to A are severed

Rule 2 (Action/Observation Exchange):

$$P(Y|\ do(A), do(B), C) = P(Y \mid do(A), B, C)$$

if Y $\coprod$ $B \mid A, C$, in the graph where incoming arrows to A, and those outgoing arrows from B are severed

Rule 3 (Insertion/Deletion of Actions):

$$P(Y|\ do(A), do(B), C) = P(Y \mid do(A), C)$$

If Y $\coprod B \mid A, C$, in the graph where incoming arrows to A and B | C are severed

Identification using front door adjustment (Neal, 2020; Pearl, 1998)

This is used in situations where there is unobserved covariate that cannot be conditioned on. The aim here is to restrict all association to those through the mediating variable. It is a two-stage process. Firstly, the effect of A on M is identified; Next the effect of M on Y is identified. This leads two the identification of A on Y.

Example: Consider this graph, there is a causal association through M and non causal association through C.

$$C \rightarrow A \rightarrow M \rightarrow Y$$

$$C \rightarrow Y$$

Front door adjustment is carried out as follows:

Step 1: Identify the effect of A (the treatment) on M (the mediator):

$$P\big(M\big|do(A)\big) = P(M|A)$$

Step 2: Identify the effect of M (the mediator) on Y (the outcome variable):

$$P(Y \mid do(M)) = \sum_{a} P(Y \mid M, A)P(A)$$

Step 3: combining the steps above to identify the effect of A on Y:

$$P(Y \mid do(A)) = \sum_{m} P(M| \, do(A))P(Y|do(M))$$

Given complete Mediation by M between A and Y; the absence of backdoor between A and M; and positivity

$$P(Y \mid do(A)) = \sum_{m} P(M| \, A)P(Y|M, A')P(A')$$

Note that in Step 1 above, the collider Y blocks any backdoor paths from A to M (Pearl, 2010). However, in step 2 above, a backdoor path flows from $M < -T < -W -> Y$. This is blocked by conditioning on A.

Identification using backdoor adjustment (Neal, 2020; Pearl, 1998)

Backdoor paths are associational, non-causal paths between the treatment and an effect that do not flow directly or through a mediator. These paths involve confounders, which create spurious associations and can bias the estimation of the causal effect. Essentially, backdoor paths are usually non-outgoing arrows that lead to unintended associations. Controlling for these confounders is necessary to accurately estimate the true causal relationship. Normally, in interventional studies, setting the treatment variable to a fixed value, severs incoming associations towards it. However, in observational data, this could be achieved by conditioning on the confounders (Neal, 2020).

The following examples are adapted from Neal, (2020) and Pearl (1995). Consider identifying the causal effect of A on Y in the presence of a confounder C.

Graph structure:

$$C \rightarrow A \rightarrow Y$$

$$C \rightarrow Y$$

To identify $P(Y \mid do(A))$, following the backdoor criterion: A set of variables C satisfies the backdoor criterion relative to A and Y if: No node in the set C is a descendant of A; C blocks every path between A and Y that contains an arrow into A.

Example using back door adjustment

Consider this graph, same as the one above,

$$C \rightarrow A \rightarrow Y$$

$$C \rightarrow Y$$

Front door adjustment is carried out as follows (Neal, 2020; Pearl, 1998):

Step 1: Identify the effect of A (the treatment) on M (the mediator):

$$P\left(M \middle| do(A)\right) = P(M|A)$$

Proof using do-calculus (Neal, 2020; Pearl, 1995 & 2010):

Starting with the expression

$$P(Y \mid do(A)) =$$

Assuming C is a sufficient adjustment set, conditioning on C gives

$$\sum_{c} P(Y \mid do(A), C = c) P(C \mid do(A)) =$$

Conditioning on C blocks all non-causal association, therefore

$$\sum_{c} P(Y \mid A, C = c) P(C \mid do(A)) =$$

In order to eliminate directed associations from A to C we use,

$$\sum_{c} P(Y \mid A, C = c) P(C)$$

From the proof above, conditioning on C blocks all non-causal association from A to Y. Since only causal associations remain, the do(A)-operator factored on Y is eliminated owing to its redundancy. Note that intervening on A ensures no incoming association to A. However, outgoing associations from A to C and Y can still occur, which may lead to colliders. Note, also, that conditioning on the ancestor to a collider is equivalent to conditioning on a collider (Pearl, 2010). This could still open the door to non-causal association between A and Y. Therefore, the do operator factorizing C is eliminated to severe any remaining association between A and C.

Thus, it results in

$$A \rightarrow Y$$

$$C \rightarrow Y$$

Appendix 3: Python's DoWhy Code for Causal Analysis

Python Code for causal analysis. PBC was used as an example. However, the same procedure is repeated for all three EI antecedents.

```
In [25]:
import matplotlib.pyplot as plt
import dowhy
from dowhy import CausalModel
import pandas as pd

# dowhy.__version__
causal_graph = """digraph{
                ESS->OR; ESS->PBC; ESS->ATB; ESS->SSN; OR->PBC; SSN->PBC; SSN->ATB;
                OR->PBC; OR->SSN; OR->ATB;  SSN->EI;  OR->EI; PBC->EI;  OR->EI; ATB->EI
            }

"""
df_model = pd.DataFrame(columns=['ESS', 'OR', 'SSN', 'ATB', 'PBC', 'EI'])
df_model.head()
covariates = ['ESS']
model = CausalModel(data=df_model, graph=causal_graph, treatment='OR', outcome='PBC', common_causes=covariates)
model.view_model()
```

Appendix 1 Specification

```
estimands = model.identify_effect(proceed_when_unidentifiable=False)
print(estimands)
```

```
Estimand type: EstimandType.NONPARAMETRIC_ATE

### Estimand : 1
Estimand name: backdoor
Estimand expression:
  d
─────(E[PBC|ESS])
d[OR]
Estimand assumption 1, Unconfoundedness: If U→{OR} and U→PBC then P(PBC|OR,ESS,U) = P(PBC|OR,ESS)

### Estimand : 2
Estimand name: iv
No such variable(s) found!

### Estimand : 3
Estimand name: frontdoor
No such variable(s) found!
```

Appendix 2 Identification

```
In [7]:  df = pd.read_csv('LV_Scores_Final.csv')
```

```
In [8]:  # Make the variable names in the dataset match the one in the dag
         causal_graph = """digraph{
                         ESS->OR; ESS->PBC; ESS->ATB; ESS->SSN; OR->PBC; SSN->PBC;
                         SSN->ATB; OR->PBC; OR->SSN; OR->ATB; SSN->EI; OR->EI; PBC->EI; OR->EI; ATB->EI
                     }


         """
         df_model = pd.DataFrame(columns=['ESS', 'OR', 'SSN', 'ATB', 'PBC', 'EI'])
         df_model.head()
         model = CausalModel(data=df, graph=causal_graph, treatment='OR', outcome='PBC', common_causes=covariates)
         model.view_model()
```

Appendix 3 Incorporating the extracted latent variable scores into the identified model

```python
estimate = model.estimate_effect(estimands, method_name="backdoor.linear_regression",
                                 effect_modifiers=[],
                                 confidence_intervals=True,
                                 test_significance=True)

print(estimate)
```

```
*** Causal Estimate ***

## Identified estimand
Estimand type: EstimandType.NONPARAMETRIC_ATE

### Estimand : 1
Estimand name: backdoor
Estimand expression:
  d
─────(E[PBC|ESS])
d[OR]
Estimand assumption 1, Unconfoundedness: If U→{OR} and U→PBC then P(PBC|OR,ESS,U) = P(PBC|OR,ESS)

## Realized estimand
b: PBC~OR+ESS
Target units: ate

## Estimate
Mean value: 0.7042201374023136
p-value: [3.14718248e-56]
95.0% confidence interval: [[0.63040598 0.7780343 ]]
```

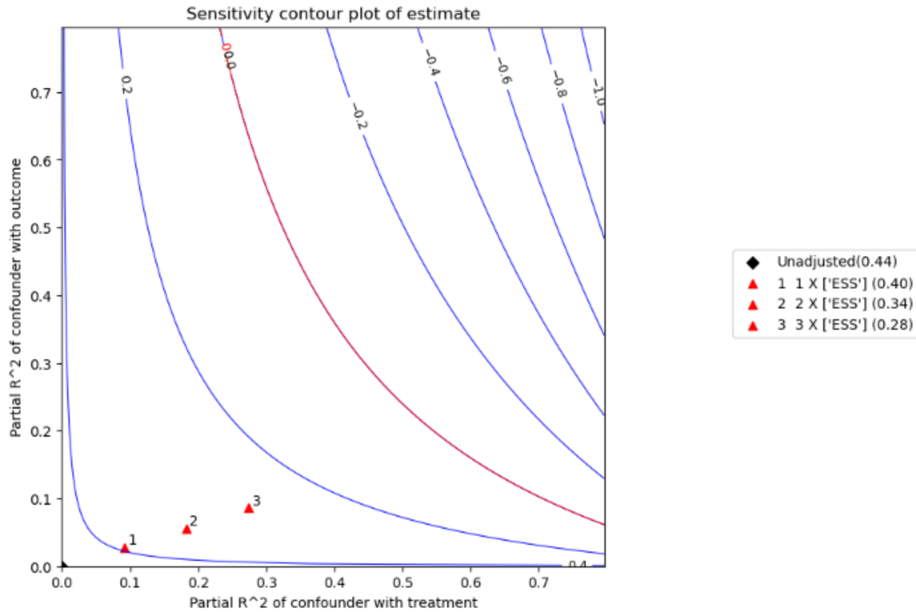
Appendix 4 Estimation

```python
In [11]:
refute_placebo_treatment = model.refute_estimate(
    estimands,
    estimate,
    method_name="placebo_treatment_refuter",
    placebo_type="permute"

    )
# New estimate shows that the effect goes down from 0.05 to 0.0095

print(refute_placebo_treatment)

# print(refute_placebo_treatment.estimated_effect/refute_placebo_treatment.new_effect)
# print(refute_placebo_treatment)
```

```
  intercept_parameter = self.model.params[0]
C:\Users\hp\anaconda3\lib\site-packages\dowhy\causal_estimators\regression_estimator.py:179: FutureWarning: Series.__geti
tem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consi
stent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  intercept_parameter = self.model.params[0]

Refute: Use a Placebo Treatment
Estimated effect:0.7042201374023136
New effect:0.006026908604452529
p value:0.8999999999999999
```

Appendix 5 Refutation (The deprecation warning is non-critical, and does not stop the program from running. It is just an alert for upcoming changes)

```
In [40]:  refute = model.refute_estimate(identified_estimand, estimate ,
                                 method_name = "add_unobserved_common_cause",
                                 simulation_method = "linear-partial-R2",
                                 benchmark_common_causes = ["ESS"],
                                 effect_fraction_on_treatment = [ 1,2,3]
                                )
```



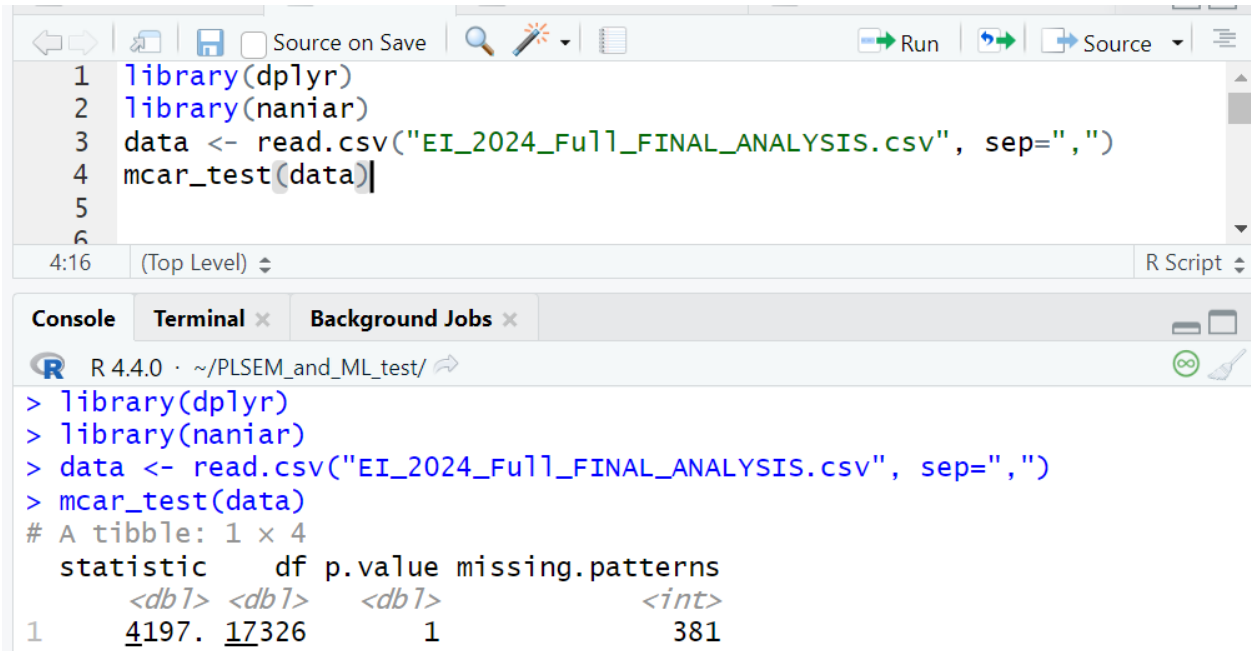
Appendix 6 Sensitivity Analysis

Appendix 4: Multiple Imputation Chained Equations for Missing data

```python
import pandas as pd
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

# Load the dataset
file_path = 'EI_2024_Full_FINAL_ANALYSIS.csv'
file_name = file_path[:-4]


data = pd.read_csv(file_path)


# Create the imputer object
imputer = IterativeImputer(max_iter=10, random_state=0)

# Apply the imputer
imputed_data = imputer.fit_transform(data)


# Convert the imputed data back to a DataFrame
imputed_data = pd.DataFrame(imputed_data, columns=data.columns)


# imputed_data.to_csv(file_name+'_MICE.csv', index=False)
rounded_MICE = imputed_data.round()
rounded_MICE.to_csv(file_name+'_ROUNDED_MICE.csv', index=False)
```

Appendix 7 Python Code for Multiple Imputation Chain Equations for the Missing data

Appendix 5: MCAR procedure using R



Appendix 8 Little's Missing Test

Appendix 6: Monte Carlo Simulation

```r
require(cSEM.DGP)
library(cSEM)
library(ggplot2)

model_dgp <- "

  ESS =~ 0.936*EM + 0.936*ET + 0.944*SS
  # Measurement models for other constructs
  OR  =~ 0.8756*OR1 + 0.900*OR2 + 0.859*OR3 + 0.763*OR4 + 0.885*OR5
  SSN =~ 0.890*SSN15 + 0.818*SSN26 + 0.677*SSN35
  ATB =~ 0.934*ATB1 +  0.918*ATB4 + 0.870*ATB5
  PBC =~ 0.841*PBC1 + 0.812*PBC2 + 0.850*PBC3 + 0.791*PBC4 + 0.830*PBC5
  EI  =~ 0.854*EI1 + 0.925*EI3 + 0.937*EI4 + 0.937*EI5

  # Structural Model
  EI  ~ 0.006*SSN + 0.564*ATB + 0.413*PBC
  ATB ~ 0.165*SSN + 0.563*OR
  PBC ~ 0.199*SSN + 0.623*OR
  SSN ~ 0.484*OR
  OR  ~ 0.337*ESS
"
#OR  ~ 0.138*Gender + 0.337*ESS + -0.206*Gender.ESS
data <- generateData(.model = model_dgp, .N=200)

model <- "
  ESS =~ EM + ET + SS
```

Appendix 9 Data Generation Process for Monte Carlo Simulation

```
model <- "
  ESS =~ EM + ET + SS
  # Measurement models for other constructs
  OR  =~ OR1 + OR2 + OR3 + OR4 + OR5
  SSN =~ SSN15 + SSN26 + SSN35
  ATB =~ ATB1 +  ATB4 + ATB5
  PBC =~ PBC1 + PBC2 + PBC3 + PBC4 + PBC5
  EI  =~ EI1 + EI3 + EI4 + EI5



  # Structural Model
  EI  ~ SSN + ATB + PBC
  ATB ~ SSN + OR
  PBC ~ SSN + OR
  SSN ~ OR
  OR  ~  ESS

"
```

Appendix 10 Model Specification for Monte Carlo Simulation

```
res_PLS <- list()
res_PLSc <- list()
i <- 1
j <- 0
set.seed(123)
while(i < 501){
  data <- generateData(.model = model_dgp, .N=500)
  res_PLSc_temp <- csem(.model = model, .data = data)
  res_PLS_temp <- csem(.model = model, .data = data, .disattenuate=FALSE)
  if(sum(verify(res_PLSc_temp)) == 0 && sum(verify(res_PLS_temp)) == 0){
    res_PLSc[[i]] <- csem(.model = model, .data = data, .resample_method = "bootstrap"
                          , .seed=123)
    res_PLS[[i]] <- csem(.model = model, .data = data, .resample_method = "bootstrap",
                         .disattenuate=FALSE, .seed=123)
    i <- i+1
  } else{
    j <- j+1
  }
}
summer500 <- summarize(res_PLSc[[500]])
print(summer500)
##assess500 <-  assess(res_PLSc[[500]])
#print(assess500)
verify500 <- verify(res_PLSc[[500]])
print(verify500)
# For sample size 500=============================================
sink("sim500Results.txt")
```

Appendix 11 Monte Carlo Simulation Algorithm for N=500