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The Effect of Artificial Intelligence Anxiety on Entrepreneurial Orientation: A Study on University Students

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Abstract: This study examines the effect of artificial intelligence anxiety and its four subdimensions (learning, job replacement, sociotechnical blindness, and AI configuration) on individual entrepreneurial orientation among university students in Türkiye. Designed as a quantitative study based on a relational survey model, data were collected via an online survey in March 2026 through convenience sampling, and the analyses were conducted on 214 valid responses. The AI Anxiety Scale (Wang & Wang, 2019; Turkish adaptation by Akkaya, Özkan, & Özkan, 2021) and the Individual Entrepreneurial Orientation (IEO) Scale (Bolton & Lane, 2012; Turkish adaptation by Ercan & Yıldırım, 2021) were used. The data were analysed through correlation, multiple regression, t-tests, and one-way ANOVA. The findings reveal that AI anxiety has a positive and statistically significant effect on IEO ($\beta = 0.330$; $p < .001$), explaining 10.9% of the total variance. Among the four AI anxiety subdimensions, sociotechnical blindness emerged as the only significant positive predictor ($\beta = 0.428$; $p < .001$). The learning subdimension had a significant negative predictive effect on proactiveness ($\beta = -0.176$; $p = .014$). Demographic analyses showed that AI anxiety differs significantly by gender, education level, and work experience, while IEO differs only by the desire to start one's own business. The study contributes theoretically by providing the first empirical test of a hybrid conceptual model integrating the facilitating–debilitating anxiety framework with Conservation of Resources theory in the context of AI anxiety, and empirically by being among the first to demonstrate this effect in the Turkish context.

Keywords: Artificial Intelligence Anxiety; Entrepreneurial Orientation; Sociotechnical Blindness; University Students; Conservation of Resources Theory.

JEL Classification: L26; O33; I23.

1. Introduction

The release of generative artificial intelligence applications such as ChatGPT to the public in late 2022 is widely regarded as the starting point of a profound transformation in information processing, content creation, and decision-support processes. A recent OECD report (2025) shows that generative AI has measurable impacts on productivity, innovation, and entrepreneurship. The same report states that it can automate or augment a significant portion of business tasks and reduce barriers to entry for starting new businesses. Yet this transformation does not generate an evenly distributed opportunity landscape. It interacts closely with individuals' skill sets, career stages, and occupational positions, opening up clear opportunities for some groups while creating perceptions of uncertainty and threat for others.

One of the most visible individual-level reflections of this dual climate has been examined through the concept of *artificial intelligence anxiety* (AI anxiety). The AI anxiety scale developed by Wang and Wang (2019) and adapted into Turkish by Akkaya, Özkan, and Özkan (2021) addresses the construct through four subdimensions: anxiety about learning AI technologies; anxiety about being forced to change jobs because of AI; sociotechnical blindness regarding the possibility that AI systems may evolve beyond human control; and configuration anxiety triggered by humanlike AI products. This multidimensional structure indicates that AI anxiety is not a uniform reaction but a layered psychological state that shapes the individual's relationship with technology at cognitive, occupational, social, and visual levels.

University students form the cohort that encounters this AI-driven transformation precisely while making their first career decisions. For this cohort, AI is at once a source of threat to the future of existing professions and an opportunity space that broadens the prospects for new venture creation and value generation. In developing economies such as Türkiye, where youth unemployment remains a prominent item on the economic agenda, university students' perceptions of the sustainability of conventional employment paths directly shape their career choices, and entrepreneurship is increasingly considered an alternative career route by a growing number of students. The potential effect of AI-related anxiety on the entrepreneurial tendencies of university students therefore emerges as a research topic of value, both theoretically and practically.

The concept of *individual entrepreneurial orientation* (IEO) provides a systematic way of examining the personal-level antecedents of entrepreneurial behaviour. The IEO scale developed by Bolton and Lane (2012) and adapted into Turkish by Ercan and Yıldırım (2021) measures an individual's tendencies along three dimensions: risk-taking, innovativeness, and proactiveness. These three dimensions are closely connected not only to entrepreneurial intent in the narrow sense, but also to broader career-oriented proactive and innovative behaviours. As such, IEO offers researchers a comprehensive and multidimensional analytical instrument for understanding the personal foundations of career behaviour.

The relationship between AI and entrepreneurial behaviour has so far been examined in only a limited number of international studies. Khalid et al. (2020), in a study conducted with university students in Malaysia, found a strong and positive relationship between AI learning and entrepreneurial orientation. Their finding provides one of the first concrete pieces of empirical evidence on the link between AI and career-oriented outcomes. In the Turkish context, the relationship between AI anxiety and career outcomes has so far been examined only with respect to perceived employability (Tuncal & Çeken, 2025) and general demographic variations (Akkaya, 2025); the effect of AI anxiety on individual entrepreneurial orientation has not yet been directly addressed. This gap points to a clear research need at both the theoretical and the empirical level, particularly when one considers that the four subdimensions of AI anxiety may exert differentiated effects on entrepreneurial behaviour.

The present study seeks to fill this gap by examining the effect of AI anxiety and its four subdimensions on individual entrepreneurial orientation among university students in Türkiye, using a quantitative research design. The study claims to make an original contribution at three levels. At the theoretical level, it proposes a hybrid conceptual framework. This framework integrates the Yerkes-Dodson law and the facilitating–debilitating anxiety framework of Alpert and Haber (1960) — both of which describe the dual effect of anxiety on behaviour — with Hobfoll's (1989, 2001) Conservation of Resources theory, which explains the individual's behavioural orientation in the face of resource threat. At the empirical level, it provides the first systematic test of the AI anxiety – IEO relationship among university students in Türkiye and examines subdimension-level differences in detail. At the practical level, it offers policy implications for entrepreneurship education programmes and career guidance services in higher education. The remainder of the paper is organised as follows: the next section presents the theoretical framework, followed by the research method, the findings obtained, a discussion of these findings in the light of the literature, and a conclusion section with recommendations.

2. Literature Review and Theoretical Framework

Anxiety is defined as a state of arousal that emerges in response to a perceived threat or unresolved fears, and that leads to distractibility (Akkaya et al., 2021). With the acceleration of technological change, this general concept of anxiety has been examined through various subforms tied to specific types of technology. *Computer anxiety* entered the literature with the spread of computers; *internet anxiety* with the expansion of communication networks; and *robot anxiety* with the rise of robotic systems (Wang & Wang, 2019). The common conceptual umbrella for these constructs is *technophobia*, which refers to abnormal levels of fear or worry concerning the effects of advanced technology (Akkaya et al., 2021). AI anxiety constitutes the most recent link in this chain. Unlike its predecessors, however, it does not concern merely a tool or an interaction partner; it captures anxiety directed towards a technological actor capable of producing autonomous decisions.

In its broad meaning, AI anxiety is defined as feelings of fear and concern regarding AI that operates outside human control (Akkaya et al., 2021). Wang and Wang (2019) treat the construct as a general emotional reaction that prevents the individual from engaging with AI. They argue that AI anxiety is fed by sources such as misperceptions of AI, uncertainty about its autonomy, and sociotechnical blindness. Another important interpretation reported by Akkaya et al. (2021) is that one of the deep roots of AI anxiety is a fundamental sense of threat to the meaning of being human, raised by the claim that computers can think. This framework positions AI anxiety beyond a technical adaptation concern; it is a phenomenon with existential and societal dimensions. This existential dimension is also supported by recent empirical findings. In a cross-sectional study conducted with 300 participants, Alkhalifah et al. (2024) reported that existential anxieties about the rapid development of AI were highly prevalent. Core existential anxiety dimensions stood out in particular, including meaninglessness (92.7%), anxiety about death (96%), and fear of condemnation arising from ethical dilemmas (93%). The same study also showed that participants who believed AI could replace their own occupations exhibited markedly higher existential anxiety scores. These findings suggest that AI anxiety is not a purely instrumental technology concern. It is instead intertwined with the individual's broader questioning of the future, their profession, and the experience of being human.

Two key features set AI anxiety apart conceptually from earlier forms of technology anxiety. First, AI is perceived not merely as a tool but as an autonomous actor capable of producing decisions on its own. This perception moves the discussion beyond the user–tool relationship and brings the human–artificial-agent relationship to the foreground. Second, AI anxiety can be experienced as a threat not only at the individual level of use, but also at the societal and

occupational levels. This expanded framework takes concrete form in the four-factor structure of the scale developed by Wang and Wang (2019).

The first subdimension of the scale, *learning*, refers to the worry an individual feels about learning to use AI technologies and products, understanding their functions, or interacting with them (Akkaya et al., 2021). This dimension reflects the cognitive and emotional load of the adaptation process to AI and rests largely on the individual's first-hand relationship with the technology.

The second subdimension, *job replacement*, captures concerns about the disappearance of professions, the devaluation of human labour, and the prospect of having to change one's career as AI applications spread (Akkaya et al., 2021; Wang & Wang, 2019). Concerns about the weakening of one's reasoning abilities as a result of dependence on AI are also evaluated under this dimension.

The third subdimension, *sociotechnical blindness*, reflects anxiety arising from focusing solely on the technology itself while overlooking the human behaviour that produces, disseminates, and sustains AI programmes (Akkaya et al., 2021). This dimension covers broad-scale sociotechnical threats such as the misuse of AI, its loss of control, malfunctions, or the potential for robotic autonomy. Individuals with sociotechnical blindness have difficulty internalising the fact that AI is a system that operates together with humans and social institutions (Akkaya et al., 2021).

The fourth subdimension, *AI configuration*, concerns particularly the experience of finding humanlike AI products (such as humanoid robots) eerie or intimidating (Akkaya et al., 2021). This dimension reflects emotional reactions to the physical and visual form of AI. Unlike the other three dimensions, it rests on a concrete and visual trigger.

The original AI Anxiety Scale was developed by Wang and Wang (2019) with 21 items. In the Turkish adaptation conducted by Akkaya et al. (2021), the four-factor structure was preserved while the number of items was reduced to 16, and the validity and reliability of the scale were confirmed across different samples. In this adapted form, the learning dimension is represented by five items, job replacement by four, sociotechnical blindness by three, and AI configuration by four.

Recent studies have shown that the subdimensions of AI anxiety can exert effects in different directions on behavioural outcomes. In a study conducted with aviation students, Tuncal and Çeken (2025) found that sociotechnical blindness positively predicted perceived employability while learning anxiety predicted it negatively, and the other two dimensions produced no significant effect. Recent research conducted on university students in Türkiye displays similar patterns. In a study with 158 finance and banking students, Akkaya (2025) found that approximately 60% of participants perceived AI as a threat to their future profession, and that this perception significantly raised their AI anxiety levels. The same study reported that the strongest relationship among the subdimensions was between job replacement and sociotechnical blindness ($r = 0.728$, $p < 0.001$). This result suggests that, for university students, these two subdimensions are conceptually and emotionally intertwined. Such differentiated findings indicate that AI anxiety should not be treated as a uniform and one-directional construct, but rather examined as a multilayered concept that needs to be disaggregated through its subdimensions. At the same time, some studies in the literature argue that anxiety is not always a one-directional factor that suppresses behaviour. Depending on the conditions and the context, it can also assume an activating function. The potential role of AI anxiety on a proactive career outcome such as individual entrepreneurial orientation should therefore be evaluated with this dual possibility in mind. The conceptual reasoning behind this argument will be placed on a theoretical foundation in the following subsections, through two complementary theories.

University students are preparing for professional life in a period when AI is profoundly transforming the world of work. This cohort is the first generation of students that perceives AI-driven threats and opportunities simultaneously, and that shapes its career decisions under this dual perception. For this reason, examining the behavioural and career-oriented outcomes of AI anxiety on this group constitutes a research focus of value, both theoretically and practically.

Entrepreneurship is regarded as one of the driving forces of economic development. It plays a critical role in the opening of new business areas, the creation of employment, and the increase of social welfare. Within this context, the academic literature focused for a long time on the question “who is an entrepreneur?” In the past four decades, however, the weight of research has shifted towards the concept of *entrepreneurial orientation*, which examines the cognitive and behavioural tendencies that drive individuals and organisations towards entrepreneurial behaviour. This concept addresses the inner tendencies that trigger entrepreneurial behaviour in a systematic way. It emphasises that entrepreneurship is shaped not only by external conditions but also by internal predispositions.

The concept of entrepreneurial orientation was first proposed by Miller (1983) as a three-dimensional construct comprising risk-taking, innovativeness, and proactiveness. It was later transformed by Covin and Slevin (1989) into an instrument that could be measured systematically at the organisational level. Covin and Slevin (1989) showed that an entrepreneurial strategic posture could positively affect firm performance even under hostile market conditions. Their study demonstrated that entrepreneurial orientation is a construct that can be empirically studied at the organisational level. In the following years, Lumpkin and Dess (1996) expanded the concept into a five-dimensional framework by adding autonomy and competitive aggressiveness to these three dimensions. They redefined entrepreneurial orientation as “the processes, practices, and decision-making activities that lead to new entry” (cited in Bolton & Lane, 2012). The meta-analysis by Rauch, Wiklund, Lumpkin, and Frese (2009), which integrated 51 different studies, found a moderate, significant, and consistent positive relationship between entrepreneurial orientation and firm performance. This meta-analysis reinforced the explanatory power of the concept at the organisational level.

The long-standing concentration of the entrepreneurial orientation literature at the organisational level led to relatively little examination of the concept's manifestations at the individual level. To fill this gap, Bolton and Lane (2012) adapted Lumpkin and Dess's (1996) five-dimensional framework to the individual level. Through a scale-development study conducted with 1,100 university students, they introduced the Individual Entrepreneurial Orientation (IEO) scale to the literature. The exploratory factor analyses showed that only three of the five dimensions — risk-taking, innovativeness, and proactiveness — produced reliable and valid measurements at the individual level. The dimensions of autonomy and competitive aggressiveness did not display sufficient internal consistency at the individual level and were therefore removed from the scale. As a result, the IEO scale, consisting of ten items, has become a widely adopted instrument for measuring entrepreneurial behavioural tendencies, particularly in samples of university students.

The first subdimension of IEO, *risk-taking*, reflects the individual's willingness to commit resources to ventures with uncertain outcomes, the courage to move into unknown areas, and the tendency to behave assertively in risky situations. As one of the basic components of the entrepreneurial process, this dimension reveals the individual's stance towards uncertainty. The second subdimension, *innovativeness*, refers to the individual's tendency to embrace new, unconventional, and original approaches. It covers not only the production of new goods or services, but also experimentation, creativity, and unconventional problem-solving methods. The third subdimension, *proactiveness*, reflects the individual's tendency to anticipate future problems, needs, or changes; to take initiative without waiting for others to act; and to evaluate opportunities in advance. This dimension involves a tendency to shape current conditions rather than merely monitor them.

Bolton and Lane's (2012) scale has been widely accepted in the international literature. A study conducted by Manik and Kusuma (2021) with 200 university students in Indonesia showed that all three subdimensions of IEO produced significant positive effects on entrepreneurial intent. This finding suggests that IEO is not only an instrument that distinguishes individuals who intend to become entrepreneurs, but also a conceptual antecedent in the development of entrepreneurial intent. The connection between IEO and the individual's emotional and psychological predispositions has also become a research area of growing interest in the literature. The regression analysis carried out by Martins, Pérez Monsalve, and Velásquez Martínez (2018) on 656 university students in Colombia showed that self-confidence positively predicted all three subdimensions of IEO, while fear of failure negatively affected the same dimensions. This finding reveals that IEO is not solely a cognitive or personality-based construct. It takes shape in interaction with the individual's emotional state — particularly with negative emotions such as anxiety and fear.

Bolton and Lane's (2012) scale was adapted into Turkish by Ercan and Yıldırım (2021). The adaptation study followed Brislin's five-stage translation procedure, and the structural validity of the scale was tested through exploratory and confirmatory factor analyses. The analyses were conducted on data collected from third- and fourth-year students enrolled in business administration programmes at state universities in Karabük, Kastamonu, Zonguldak, and Bandırma. The results showed that the original three-factor structure of the scale was preserved, that the total variance explained was approximately 61%, and that the KMO value exceeded 0.85. These findings demonstrate that IEO is a reliable and valid measurement instrument for samples of Turkish university students.

In sum, IEO is a construct that measures the individual's entrepreneurial behavioural tendency through the dimensions of risk-taking, innovativeness, and proactiveness. It has been psychometrically validated in both the international and the Turkish literature. In the present study, this construct will be used as the dependent variable to examine the potential effects of AI anxiety on university students. The question of how the potential effect of AI anxiety on IEO can be theoretically justified — that is, how a negative emotional state such as anxiety can be expected to feed proactive entrepreneurial behaviour — will be answered in the following two subsections through two complementary theoretical frameworks.

The intuitive understanding of anxiety holds that it always affects performance and behaviour in a suppressive way. Yet one of the most well-established findings in the psychology literature is that the relationship between anxiety and behavioural outcomes is not one-directional or linear. It is multilayered and sensitive to context. Two foundational theoretical frameworks have demonstrated this dual nature: the classical arousal–performance law of Yerkes and Dodson (1908) and the facilitating–debilitating anxiety distinction of Alpert and Haber (1960). These two frameworks provide the first theoretical basis for the present study's argument concerning the potential positive effect of AI anxiety on individual entrepreneurial orientation.

The classical experiments conducted by Yerkes and Dodson (1908) on Japanese dancing mice showed that the relationship between physiological arousal level and learning performance is not linear. It instead displays an inverted-U-shaped curve. The authors found that at very low levels of arousal the organism cannot reach sufficient motivation for the task, and that at very high levels of arousal performance declines because of distraction and disruption of cognitive processes. Moderate levels of arousal, by contrast, optimise performance. This law was subsequently expanded with nuances based on task difficulty: the optimal arousal point was argued to be lower for complex, cognitively demanding tasks and higher for simple, mechanical ones. Although the law of Yerkes and Dodson (1908) was not built directly on the concept of “anxiety”, it formed the theoretical ground for the subsequent literature that treats anxiety as a type of arousal. It became a reference point in studies on the behavioural outcomes of anxiety.

More than half a century after the general law of Yerkes and Dodson (1908), Alpert and Haber (1960) addressed anxiety directly in the context of academic performance. They argued that measuring anxiety as a one-directional construct weakened analytical power. The authors operationalised anxiety along two distinct dimensions through the Achievement Anxiety Test (AAT) they developed. *Facilitating anxiety* refers to the functional anxiety that activates the individual in the face of a task, focuses attention, and channels effort towards preparation. *Debilitating anxiety*, by contrast, reflects the dysfunctional anxiety that disrupts performance, distracts attention, and leads to task-avoidance behaviour. In a sample of Stanford University students, Alpert and Haber (1960) found that the facilitating anxiety dimension showed a significant positive relationship with academic achievement, while the debilitating anxiety dimension showed a significant negative relationship. More importantly, this study showed that the two anxiety dimensions are statistically distinct constructs that can coexist in the same individual at the same time. This finding revealed that the real behavioural effects of anxiety can be hidden when measured with a single general scale. A measurement approach that disaggregates the functional and dysfunctional dimensions can offer more refined predictive information.

When the frameworks of Yerkes and Dodson (1908) and Alpert and Haber (1960) are evaluated together, the emerging theoretical reasoning can be summarised as follows. Anxiety is not a fixed and one-directional psychological state. It is a context-sensitive form of arousal that varies in interaction with the individual's coping capacity, the type of task, and the context. Anxiety levels that produce sufficiently intense arousal but do not exceed the individual's coping capacity can assume a functional role: they activate the individual, push towards preparation, and produce behavioural outcomes. By contrast, anxiety levels that exceed coping capacity and are perceived as uncontrollable lead to withdrawal, avoidance behaviour, and a decline in performance. This dual nature shows that the direction and magnitude of the anxiety–behaviour relationship are not predetermined constants. They are shaped by conditions.

This theoretical framework has a clear extension for AI anxiety. While developing the AI anxiety scale, Wang and Wang (2019) drew explicitly on the Yerkes-Dodson law in their conceptual framework. They argued that AI-related anxiety cannot in every case be evaluated as a factor that suppresses the individual. On the contrary, at certain levels it may assume an activating, motivational, and behaviourally functional role. This explicit conceptual stance provides indirect theoretical support, at the level of the scale's developers, for the present study's core proposition that AI anxiety can produce a significantly positive effect on IEO.

The Yerkes-Dodson and Alpert-Haber frameworks offer a strong theoretical basis for explaining *why* anxiety does not always suppress behaviour. They do not, however, directly answer the question of *why* an individual might be drawn specifically towards entrepreneurial behaviours when faced with the threat of AI. In other words, the existing frameworks indicate the *possibility* that anxiety can take on an activating function. They do not provide a mechanism explaining the *direction* of this activation — why the individual would choose active venture over passive adaptation or seek opportunity over withdrawal. The theoretical framework that complements this gap by laying out such a mechanism is Hobfoll's Conservation of Resources theory, addressed in the following section.

The Yerkes-Dodson law and the facilitating–debilitating anxiety distinction of Alpert and Haber (1960), addressed in Section 2.3, establish theoretically that anxiety does not always suppress behaviour. Depending on the conditions, it can also assume a functional and activating role. While these frameworks are strong in explaining the *possibility* that anxiety can take on an activating function, they do not provide a direct mechanism for why an individual moves specifically towards entrepreneurial behaviours when faced with threat — choosing active investment over passive adaptation, or the search for opportunity over withdrawal. The theoretical framework that complements this gap by laying out such a mechanism is Hobfoll's (1989) Conservation of Resources theory (COR).

Hobfoll (1989) proposed COR as an alternative framework, arguing that classical stress theories — which focus on individual perceptual processes and cognitive appraisals — could not adequately explain human behaviour. The core proposition of COR is straightforward: individuals possess a fundamental motivation to acquire, protect, and maintain resources they value. Stress arises when these resources are actually lost, are under threat of loss, or when invested resources fail to yield the expected return. This approach repositions stress not merely as a subjective cognitive appraisal. It treats stress as a process tied to the fate of resources to which the individual objectively assigns value, and a process with motivational and behavioural consequences.

Hobfoll's (1989) concept of resources has a wide scope and is treated under four main categories: *objects* (property, physical instruments); *conditions* (social positions such as employment, marriage, or seniority); *personal characteristics* (self-efficacy, self-esteem, hope, optimism); and *energies* (time, money, knowledge). For university students in particular, future employment, occupational position, career development opportunities, and professional competencies are among the most basic resources. In the current context, where AI is profoundly transforming working life, these resources are under direct perceived threat from the standpoint of the COR framework.

The central behavioural proposition of the theory is the principle of *resource investment*. Hobfoll (1989, 2001) argues that individuals who experience resource loss, or who perceive a threat of loss, transform their existing resources into investments in order not to suffer further losses or to compensate for future ones. This investment is not a passive adaptive response. It is an active, goal-directed strategy aimed at producing new resources. Resource investment constitutes one of the most distinctive contributions of the theory: in the face of stress, it predicts forward-looking action rather than withdrawal. This proposition provides direct theoretical support for the present study's core argument concerning the potential positive effect of AI anxiety on IEO. University students with high AI anxiety, perceiving that their existing resource configurations (conventional career paths, standard employment expectations) are no longer secure, may strengthen their entrepreneurial tendencies as a way to generate new resources.

In the extended version of COR, Hobfoll (2001) integrated the concept of *proactive coping* into the theoretical framework. Reactive coping consists of responses to a stressor that already exists. Proactive coping, by contrast, refers to behaviours of resource accumulation, preparation, and the design of preventive actions in anticipation of threats that have not yet emerged. This concept overlaps directly, at the conceptual level, with proactiveness — one of the three subdimensions of IEO, the dependent variable of the present study. In the framework of Bolton and Lane (2012), proactiveness refers to the tendency to anticipate future problems and opportunities and to take action. Hobfoll's (2001) concept of proactive coping predicts the same behavioural construct in functional terms. This conceptual overlap reinforces the explanatory power of the COR framework for entrepreneurial behaviours in the AI context.

Another important conceptual contribution of Hobfoll (2001) is the proposition of *resource gain and loss spirals*. According to the author, individuals who successfully accumulate resources and convert them into investments become more resilient to future threats and tend to accumulate even more resources; this process produces a gain spiral. By contrast, individuals who suffer resource loss become increasingly fragile and more exposed to further losses. The three dimensions of IEO — *risk-taking* (investment in creating new resources under uncertainty), *innovativeness* (developing alternative ways of producing resources), and *proactiveness* (preventive preparation against future threats) — overlap structurally with the propositions of resource investment, proactive coping, and gain spirals in COR theory. This suggests that IEO can be interpreted not only as a personality tendency but also as a resource-based coping strategy.

The theoretical value of the COR framework for the present study is twofold. First, it offers a specific prediction about the direction of the anxiety–behaviour relationship: to the extent that perceived threat leads to resource investment and proactive coping behaviours, AI anxiety can positively affect entrepreneurial orientation. Second, when this prediction is combined with the Yerkes-Dodson and Alpert-Haber frameworks addressed in Section 2.3, an integrated theoretical structure emerges. This structure explains both the possibility that anxiety does not suppress behaviour and the mechanism by which such behaviour is realised specifically in an entrepreneurial direction. The synthesis of the two theoretical frameworks, the potentially differentiated effects of AI anxiety subdimensions on IEO, and the *a priori* justification of the present study's hypotheses will be addressed in the following subsection.

The Yerkes-Dodson law and the facilitating–debilitating anxiety distinction of Alpert and Haber (1960), addressed in Section 2.3, together with Hobfoll's (1989, 2001) Conservation of Resources theory addressed in Section 2.4, each explain particular aspects of the potential effect of AI anxiety on individual entrepreneurial orientation. When evaluated together, however, the two frameworks form the integrated theoretical structure required for the *a priori* justification of the present study's hypothesis directions. In this hybrid framework, the first group of theories provides a prediction about the *possibility* of the effect of anxiety on behaviour — anxiety can assume a functional role depending on the conditions. The second theory provides a mechanism for the *direction* of this functional behaviour — when faced with perceived resource threat, individuals exhibit active resource investment and proactive coping behaviours. This synthesis forms the basis of the theoretical expectation that AI anxiety can produce a positive effect on IEO.

The implications of the hybrid theoretical framework for the three subdimensions of IEO can be summarised as follows. The risk-taking dimension overlaps directly with Hobfoll's (1989) resource investment proposition: transforming existing resources into investments to produce new resources under uncertain conditions is the central behavioural proposition of the COR framework. Innovativeness, when interpreted as the tendency to discover alternative ways of producing resources and to generate non-conventional solutions, is the behavioural manifestation of a resource diversification strategy. Proactiveness, in turn, displays a structure that overlaps conceptually with Hobfoll's (2001) concept of proactive coping; it covers anticipatory preparation and preventive actions against future threats. This three-part structure suggests that IEO is not merely a personality tendency. It can also be interpreted as a resource-based coping behaviour.

The predictions of the hybrid framework are also supported by recent empirical findings. Khalid et al. (2020), in a partial least squares structural equation modelling analysis with data collected from university students in Malaysia, found that AI learning had a strong and positive effect on entrepreneurial orientation ($\beta = 0.848$; $p < 0.001$). In the same study, entrepreneurial orientation significantly predicted entrepreneurial performance through the processes of exploration and exploitation. The independent variable in Khalid et al.'s (2020) study was AI *learning* (that is, an educational environment in which the student is exposed intensively to AI), while in the present study it is AI *anxiety*; nonetheless, both constructs imply that the individual is in intensive cognitive and emotional interaction with AI. This parallel provides empirical support for the prediction that intensive engagement with AI — whether through exposure or through anxiety — can positively activate entrepreneurial orientation.

The most direct empirical evidence for the proposition that AI anxiety subdimensions can produce differentiated effects on behavioural outcomes comes from the study of Tuncal and Çeken (2025), conducted on aviation students in Türkiye ($n = 909$). In a multiple linear regression analysis, the authors found that the sociotechnical blindness dimension significantly predicted perceived employability in a positive direction ($\beta = 0.130$; $p = 0.009$), while the learning anxiety dimension predicted it in a negative direction ($\beta = -0.142$; $p = 0.001$). The job replacement and AI configuration dimensions didn't produce a significant effect. This

differentiated pattern demonstrates the methodological necessity of examining AI anxiety not as a uniform construct but in a disaggregated manner through its subdimensions. It also shows that the unique logic of each subdimension on behavioural outcomes needs to be theoretically justified separately.

A complementary finding regarding the proposition that the relationship between AI anxiety and career-oriented outcomes is established not directly but through psychological resources comes from the structural equation modelling analysis conducted by Li, Ouyang, and Lin (2025) on Chinese university students. The authors showed that the effect of AI attitudes and AI literacy on job-seeking anxiety operates through career self-efficacy. This finding offers a mechanism consistent with Hobfoll's (2001) framework of personal resources (especially self-efficacy) and suggests that the AI-career relationship operates through the individual's psychological resource configuration. While the present study doesn't directly measure mediator variables such as career self-efficacy, IEO itself functions as a similar resource — a behavioural indicator of proactive coping capacity.

An important reference for the sensitivity of individual entrepreneurial orientation to emotional variables comes from the Colombian sample of Martins, Pérez Monsalve, and Velásquez Martinez (2018), mentioned in Section 2.2. The authors found that self-confidence positively and significantly predicted the three subdimensions of IEO, while fear of failure negatively predicted the same dimensions. This finding shows that the effect of anxiety-like negative emotions on IEO is not uniform. It is shaped by the type, content, and context of the emotion. In the context of the present study, this suggests that whether AI anxiety will assume a “performance-oriented facilitating anxiety” function or an “avoidance-oriented debilitating anxiety” function may differ across subdimensions.

When the hybrid theoretical framework and the existing empirical findings are evaluated together, the *a priori* expectations regarding the potential effects of the four AI anxiety subdimensions on IEO can be justified as follows.

Learning anxiety reflects a perceived threat to the individual's personal competence resource. In Hobfoll's (1989) framework, such a threat can trigger a resource investment response, but it can equally lead to resource conservation and avoidance behaviour. The negative effect found by Tuncal and Çeken (2025) for learning anxiety supports the possibility that this dimension may serve a debilitating function. However, it is difficult to establish a clear conceptual prediction regarding the direction of the effect on IEO. For this reason, formulating the hypothesis without specifying a direction for this subdimension is methodologically more consistent.

Job replacement anxiety reflects the most direct perceived threat to the individual's career and employment resources. Hobfoll's (1989) resource investment proposition has the strongest explanatory power for this dimension: individuals who perceive that their existing career expectations are under threat from AI may turn to entrepreneurial orientation as a strategy for creating new resources. Within this logic, job replacement anxiety is expected to produce a positive effect on IEO.

Sociotechnical blindness reflects a broad-scale perceived threat that AI systems will develop in an uncontrolled, unpredictable, and socially detached manner. The finding of Tuncal and Çeken (2025) is the strongest empirical evidence that this dimension serves a facilitating function on behavioural outcomes. Individuals high in this dimension may turn to producing alternative career paths in response to a systemic threat they perceive as uncontrollable. Sociotechnical blindness is therefore expected to produce a positive effect on IEO.

The AI configuration dimension reflects a concrete and visual anxiety about humanlike AI products. When read as a “human replacement” threat, this dimension may trigger a resource investment response and produce a positive effect on IEO. However, the fact that Tuncal and Çeken (2025) didn't find a significant effect for this dimension suggests that the expected effect

may not directly translate into career-oriented behaviours, given the concrete and visual nature of the subdimension. Nonetheless, based on the general logic of the hybrid theoretical framework, the hypothesis is formulated that this dimension produces a positive effect on IEO.

The directional differences across these subdimension hypotheses strengthen the position of the present study against the HARK (hypothesising after the results are known) critique. The hypothesis directions have been justified *a priori* on the basis of both the hybrid theoretical framework (Yerkes-Dodson + Alpert-Haber + Hobfoll) and the empirical findings obtained from Turkish and international samples. The decision not to specify a direction for the learning anxiety hypothesis in particular reflects the transparent reporting of the genuine uncertainty among the subdimensions and was preferred for reasons of methodological honesty.

In light of the hybrid theoretical framework, the supporting empirical findings, and the *a priori* justification at the subdimension level, the structure of the present study's hypotheses is summarised holistically in the research model presented in Figure 1.

In light of the hybrid theoretical framework discussed in Sections 2.3 and 2.4 and the empirical findings presented in Section 2.5, the following hypotheses have been developed to test the effect of AI anxiety on individual entrepreneurial orientation and to examine whether these two constructs differ according to demographic characteristics.

When the facilitating anxiety framework of Yerkes and Dodson (1908) and Alpert and Haber (1960) is brought together with Hobfoll's (1989, 2001) Conservation of Resources theory and Khalid et al.'s (2020) empirical finding documenting a positive relationship between AI and entrepreneurial orientation, individuals high in AI anxiety are expected to turn towards entrepreneurial behaviours in order to protect the resources they perceive as threatened and to create new ones. Accordingly, the core hypothesis of the present study is formulated as follows:

H1: AI anxiety has a positive and significant effect on individual entrepreneurial orientation.

The subhypotheses are constructed by considering Tuncal and Çeken's (2025) findings on aviation students in Türkiye, which suggest that the four AI anxiety subdimensions can produce differentiated effects on behavioural outcomes, together with the position of each subdimension within Hobfoll's (1989) resource framework. Learning anxiety reflects a perceived threat to the individual's personal competence resource. At the theoretical level, this dimension can assume both functional and dysfunctional roles, and a direction is therefore not specified. The job replacement and sociotechnical blindness dimensions represent the threat perceptions that most strongly trigger the resource investment response, and a positive direction is therefore expected. While empirical support for the AI configuration dimension is comparatively weaker, a positive direction is also predicted, based on the general logic of the hybrid theoretical framework.

H1a: The learning subdimension of AI anxiety has a significant effect on individual entrepreneurial orientation.

H1b: The job replacement subdimension of AI anxiety has a positive and significant effect on individual entrepreneurial orientation.

H1c: The sociotechnical blindness subdimension of AI anxiety has a positive and significant effect on individual entrepreneurial orientation.

H1d: The AI configuration subdimension of AI anxiety has a positive and significant effect on individual entrepreneurial orientation.

Recent studies have reported that the level of AI anxiety differs according to demographic characteristics — particularly gender, year of study, work experience, and whether the student has taken an entrepreneurship course. These patterns have been observed both in samples of university students in Türkiye (Akkaya, 2025; Tuncal & Çeken, 2025) and in international samples (Alkhalifah et al., 2024). The literature similarly indicates that individual

entrepreneurial orientation is sensitive to demographic variables (Bolton & Lane, 2012; Doğrul et al., 2023). Accordingly, the present study tests whether these two constructs differ according to demographic characteristics in an exploratory and complementary manner.

H2a: AI anxiety differs significantly according to demographic characteristics.

H2b: Individual entrepreneurial orientation differs significantly according to demographic characteristics.

The research design, sampling strategy, data collection instruments, and statistical analysis methods that will be used to test the seven hypotheses listed above are detailed in the following section.

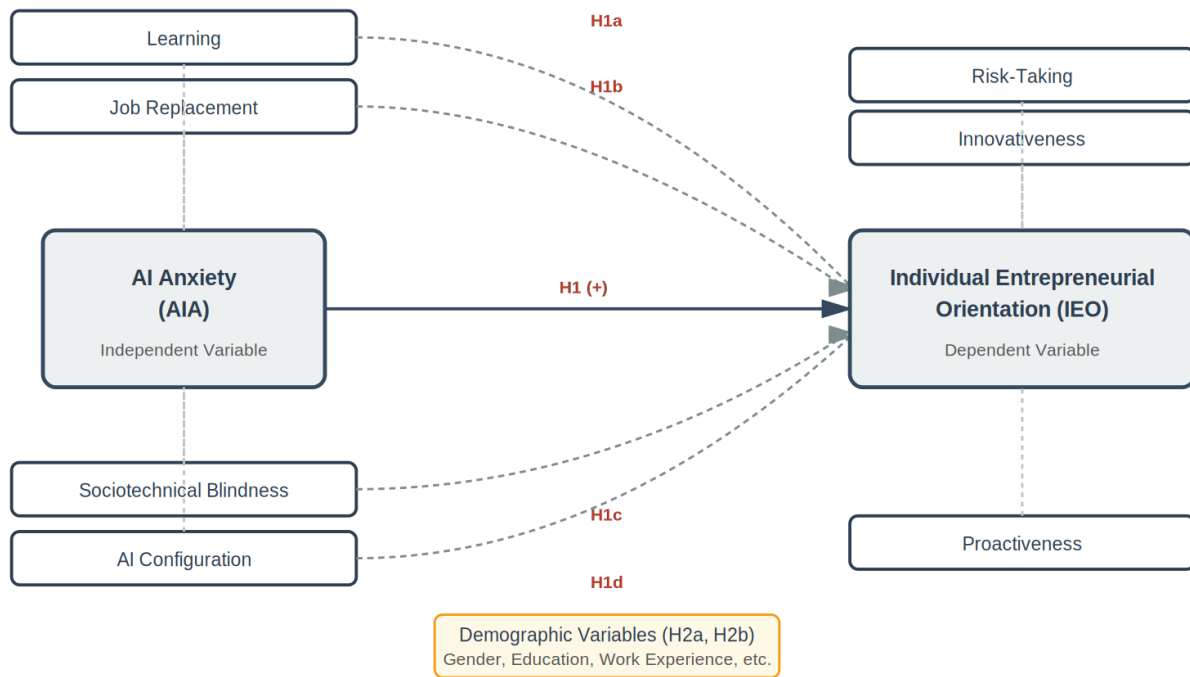


Fig. 1. Research Model

Source: Authors' own elaboration.

3. Methodology

3.1. Aim, Model, and Hypotheses of the Research

The aim of this study is to examine the effect of AI anxiety and its four subdimensions (learning, job replacement, sociotechnical blindness, and AI configuration) on individual entrepreneurial orientation among university students in Türkiye, and to determine whether these two constructs differ according to demographic characteristics. The study was designed using a quantitative research design based on the relational survey model. In the model, AI anxiety is positioned as the independent variable and individual entrepreneurial orientation as the dependent variable. The hypotheses of the study were formally presented in Section 2.6, and the research model is summarised in Figure 1.

3.2. Ethics Committee Approval

The study was approved by the Ethics Committee of Manisa Celal Bayar University at its meeting dated 26.02.2026 (number 2026/03), under decision number 19. During data collection, participants were informed about the aim of the research, the principle of voluntary participation, the assurance of anonymity, and their right to withdraw at any time. Informed consent was obtained from all participants through the online survey. Personal data of participants weren't recorded at any stage; only anonymous demographic information and scale responses were used in the analyses.

3.3. Population and Sample

The population of the study consists of students enrolled at the associate's and bachelor's level in state universities in Türkiye. The sample was determined through the convenience sampling method, and data were collected through an online survey in March 2026. A total of 234 participants were reached during data collection, but a stepwise screening was applied to the dataset in line with the scope of the ethics committee approval and the target population of the study. Within this scope, one participant under the age of 18, nine participants whose education level was unclear, six participants enrolled at the master's or doctoral level, and four participants who weren't currently university students were excluded from the analyses. As a result, the final analyses were conducted on 214 valid questionnaires.

The adequacy of the sample size for the planned analyses was evaluated against two criteria. First, given that the total number of items in the scales used in the study was 26, the sample size of 214 corresponds to 8.2 participants per item, which exceeds the minimum of five participants per item recommended by Kline (2011). Second, when assessed against the formula $N \geq 50 + 8m$ (where m is the number of predictors) suggested by Tabachnick and Fidell (2013) for regression analyses, the four-predictor multiple regression requires a minimum of 82 participants. The sample of 214 well exceeds this threshold.

The sample displays a fairly homogeneous distribution in terms of age profile; 98.1% of participants are in the 18–24 age range. For this reason, conducting demographic difference tests on the age variable was not considered methodologically appropriate. Age is therefore reported only as a descriptive characteristic of the sample.

3.4. Data Collection Instruments

The data collection instrument used in the research was a survey form consisting of three sections. The first section contained nine questions designed to identify the demographic characteristics of the participants (gender, age, education level, university, work experience, internship status, whether the student had taken an entrepreneurship course, and whether the student wanted to start their own business). The second and third sections contained the two main scales of the study.

Artificial Intelligence Anxiety Scale (AIAS). The scale developed by Wang and Wang (2019) and adapted into Turkish by Akkaya, Özkan, and Özkan (2021) was used. The scale consists of 16 items and four subdimensions: learning (5 items), job replacement (4 items), sociotechnical blindness (3 items), and AI configuration (4 items). The scale is in 5-point Likert format, with response options ranging from “1 = Strongly Disagree” to “5 = Strongly Agree”. In the Turkish adaptation study by Akkaya, Özkan, and Özkan (2021), the Cronbach Alpha coefficient for the entire scale was reported as 0.937.

Individual Entrepreneurial Orientation Scale (IEO). The scale developed by Bolton and Lane (2012) and adapted into Turkish by Ercan and Yıldırım (2021) was used. The scale consists of 10 items and three subdimensions: risk-taking (3 items), innovativeness (4 items), and proactiveness (3 items). Consistent with the AIAS, this scale is also in 5-point Likert format,

with response options ranging from “1 = Strongly Disagree” to “5 = Strongly Agree”. Ercan and Yıldiran (2021) demonstrated that the original three-factor structure of the scale was confirmed in a sample of Turkish university students and that the scale was psychometrically reliable.

3.5. Data Analysis

Data analyses were carried out using IBM SPSS Statistics 27. The internal consistency reliability of the scales was evaluated through the Cronbach Alpha coefficient. For the construct validity of the scales, the Kaiser-Meyer-Olkin (KMO) sampling adequacy measure and Bartlett's test of sphericity were applied. Whether the data displayed a normal distribution was examined through skewness and kurtosis values, with the ± 2 reference range recommended by George and Mallery (2010) used as the criterion.

Descriptive analyses included frequency and percentage distributions for demographic variables, and means and standard deviations for the subdimensions and total scores of the scales. The direction and magnitude of relationships among variables were examined through Pearson correlation analysis. The effect of AI anxiety on individual entrepreneurial orientation was tested through simple linear regression (on total scores), while the effects of the four AI anxiety subdimensions on the total IEO score and on the three IEO subdimensions were tested through four separate multiple linear regression analyses. Within the assumptions of the multiple regression analyses, the multicollinearity issue among variables was checked through the variance inflation factor (VIF) and tolerance values, and the independence of the error terms through the Durbin-Watson statistic.

Differences in AI anxiety and individual entrepreneurial orientation levels according to demographic variables were examined using the independent samples t-test for two-category variables and one-way analysis of variance (ANOVA) for variables with more than two categories. The level of statistical significance was set at $p < 0.05$ for all analyses.

4. Findings

4.1. Demographic Characteristics of Participants

The frequency and percentage distributions for the demographic characteristics of the 214 university students who participated in the research are presented in Table 1. Of the participants, 54.2% ($n = 116$) are women and 45.8% ($n = 98$) are men. When the age distribution is examined, the great majority of participants (98.1%) are in the 18–24 age range. In terms of education level, 59.8% of the sample ($n = 128$) are bachelor's-level students and 40.2% ($n = 86$) are associate's-level students. Looking at the distribution by university, 69.6% of participants ($n = 149$) are enrolled at Manisa Celal Bayar University, 24.3% ($n = 52$) at Isparta University of Applied Sciences, and 4.7% ($n = 10$) at Trakya University; the remaining three participants come from other universities. The proportion of participants with work experience is 69.6% ($n = 149$), the proportion with internship experience is 30.8% ($n = 66$), and the proportion who have taken an entrepreneurship course is 27.6% ($n = 59$). The proportion of participants who reported a desire to start their own business is 73.4% ($n = 157$).

Table 1. Demographic Characteristics of the Participants ($n = 214$)

Variable	Category	n	%
Gender	Female	116	54.2
	Male	98	45.8
Age	18–24	210	98.1
	25 and above	4	1.9
Education Level	Associate's	86	40.2
	Bachelor's	128	59.8

Table 1 (cont.)

University	Manisa CBU	149	69.6
	Isparta UAS	52	24.3
	Trakya	10	4.7
	Other	3	1.4
Work Experience	Yes	149	69.6
	No	65	30.4
Internship Experience	Yes	66	30.8
	No	148	69.2
Entrepreneurship Course	Taken	59	27.6
	Not Taken	155	72.4
Desire to Start Own Business	Yes	157	73.4
	No	57	26.6

4.2. Validity and Reliability Analyses of the Scales

The Kaiser-Meyer-Olkin (KMO) sampling adequacy value of the AI Anxiety Scale was found to be 0.917, and Bartlett's test of sphericity was statistically significant ($\chi^2 = 3480.254$; $df = 120$; $p < 0.001$). These values indicate that the scale is highly suitable for factor analysis. For the IEO Scale, the KMO value is 0.927, and Bartlett's test of sphericity is again significant ($\chi^2 = 1843.499$; $df = 45$; $p < 0.001$). For both scales, the KMO values obtained considerably exceed the threshold of 0.60 recommended by Tabachnick and Fidell (2013).

The internal consistency reliability of the scales was evaluated through the Cronbach Alpha coefficient. The total Cronbach Alpha value of the AI Anxiety Scale was 0.943; for the subdimensions, the values were 0.919 for learning, 0.884 for job replacement, 0.810 for sociotechnical blindness, and 0.930 for AI configuration. The total Cronbach Alpha value of the IEO Scale was 0.945; for the subdimensions, the values were 0.884 for risk-taking, 0.901 for innovativeness, and 0.902 for proactiveness. All values exceed the "high reliability" threshold ($\alpha > 0.80$) specified by George and Mallery (2010).

Table 2. Reliability and KMO Values of the Scales

Scale / Subdimension	Number of Items	Cronbach Alpha	KMO
AI Anxiety (Total)	16	0.943	0.917
Learning	5	0.919	—
Job Replacement	4	0.884	—
Sociotechnical Blindness	3	0.810	—
AI Configuration	4	0.930	—
Individual Entrepreneurial Orientation (Total)	10	0.945	0.927
Risk-Taking	3	0.884	—
Innovativeness	4	0.901	—
Proactiveness	3	0.902	—

4.3. Descriptive Statistics of the Scales

The total mean score of the AI Anxiety Scale was calculated as 2.7415 ($SD = 0.90611$). On a 5-point Likert scale, this value indicates a below-average level of AI anxiety. Among the subdimensions, the highest means were observed for sociotechnical blindness ($M = 3.20$; $SD = 1.12$) and job replacement ($M = 3.09$; $SD = 1.07$); the lowest mean was observed for the learning dimension ($M = 2.17$; $SD = 0.98$). The total mean score of the IEO Scale was 3.4234

(SD = 0.99930), indicating an above-average entrepreneurial tendency. Among the subdimensions, proactiveness displayed the highest mean ($M = 3.58$; $SD = 1.06$), followed by innovativeness ($M = 3.39$; $SD = 1.07$) and risk-taking ($M = 3.31$; $SD = 1.10$). The skewness and kurtosis values were within the ± 1 range, indicating that the data displayed a normal distribution.

Table 3. Descriptive Statistics of the Scales

Variable	Mean	Standard Deviation	Skewness	Kurtosis
AI Anxiety Total	2.7415	0.90611	0.01	-0.32
Learning	2.17	0.98	0.68	-0.15
Job Replacement	3.09	1.07	-0.21	-0.52
Sociotechnical Blindness	3.20	1.12	-0.38	-0.55
AI Configuration	2.77	1.17	0.12	-0.72
IEO Total	3.4234	0.99930	-0.29	-0.42
Risk-Taking	3.31	1.10	-0.18	-0.46
Innovativeness	3.39	1.07	-0.28	-0.38
Proactiveness	3.58	1.06	-0.42	-0.30

4.4. Correlation Analysis

The relationship between AI anxiety and individual entrepreneurial orientation was examined through Pearson correlation analysis. As shown in Table 4, a positive, close-to-moderate, and statistically significant relationship was found between the AI anxiety total score and the IEO total score ($r = 0.330$; $p < 0.001$). When examined at the subdimension level, the highest correlation with the IEO total score was with the sociotechnical blindness dimension ($r = 0.419$; $p < 0.001$). Lower correlations were found with job replacement ($r = 0.308$; $p < 0.001$), AI configuration ($r = 0.301$; $p < 0.001$), and learning ($r = 0.118$; $p = 0.084$). The relationship between the learning dimension and IEO is just above the significance threshold.

Table 4. Correlations among the Subdimensions of AI Anxiety and IEO ($n = 214$)

	1	2	3	4	5	6	7	8
1. AI Anxiety Total	1							
2. Learning	0.76	1						
3. Job Replacement	0.87	0.55	1					
4. Sociotechnical Blindness	0.84	0.49	0.73	1				
5. AI Configuration	0.86	0.57	0.71	0.68	1			
6. IEO Total	0.33	0.12	0.31	0.42	0.30	1		
7. Risk-Taking	0.28	0.11	0.28	0.33	0.26	0.87	1	
8. Innovativeness	0.33	0.15	0.32	0.42	0.29	0.93	0.77	1

Note: $p < 0.05$; $p < 0.001$.

4.5. The Effect of AI Anxiety on IEO: Simple Linear Regression

To test hypothesis H1, a simple linear regression analysis was conducted with AI anxiety as the independent variable and individual entrepreneurial orientation as the dependent variable. The results revealed that AI anxiety has a positive and statistically significant effect on IEO ($\beta = 0.330$; $t = 5.084$; $p < 0.001$). The explanatory power of the model is $R^2 = 0.109$, and the F test is significant ($F(1, 212) = 25.848$; $p < 0.001$). This result shows that a one-unit increase in AI anxiety is associated with an increase of approximately 0.33 units in IEO, and that AI anxiety explains approximately 10.9% of the total variance in IEO. *Hypothesis H1 was supported.*

Table 5. The Effect of AI Anxiety on IEO (Simple Regression)

Independent Variable	β	t	p	R ²	F	p (F)
AI Anxiety Total	0.330	5.084	<0.001	0.109	25.848	<0.001

Dependent variable: IEO Total

4.6. The Effect of AI Anxiety Subdimensions on IEO: Multiple Regression

To test hypotheses H1a, H1b, H1c, and H1d, a multiple linear regression analysis was conducted with the four subdimensions of AI anxiety as independent variables and the total IEO score as the dependent variable. In testing the assumption of multicollinearity, the variance inflation factor (VIF) values ranged between 1.33 and 3.52, all of which are below the acceptable threshold ($VIF < 10$).

As shown in Table 6, the model was significant overall ($R^2 = 0.193$; $F(4, 209) = 12.465$; $p < 0.001$), and the four subdimensions together explain approximately 19.3% of the variance in IEO. When the individual coefficients are examined, sociotechnical blindness emerges as a positive, significant, and strong predictor of IEO ($\beta = 0.428$; $t = 4.361$; $p < 0.001$). The learning ($\beta = -0.074$; $p = 0.287$), job replacement ($\beta = 0.008$; $p = 0.930$), and AI configuration ($\beta = 0.071$; $p = 0.397$) subdimensions weren't significant predictors. In line with these findings, *hypothesis H1c (the positive effect of sociotechnical blindness on IEO) was supported, while hypotheses H1a, H1b, and H1d weren't supported.*

Table 6. The Effect of AI Anxiety Subdimensions on IEO Total (Multiple Regression)

Independent Variable	β	t	p	VIF
Learning	-0.074	-1.067	0.287	1.57
Job Replacement	0.008	0.088	0.930	2.68
Sociotechnical Blindness	0.428	4.361	<0.001	2.18
AI Configuration	0.071	0.847	0.397	2.32

$R^2 = 0.193$; $F(4, 209) = 12.465$; $p < 0.001$;

Dependent variable: IEO Total.

4.7. The Effect of AI Anxiety Subdimensions on IEO Subdimensions

To examine the specific effects of AI anxiety subdimensions on each subdimension of IEO, three separate multiple regression analyses were carried out. In the analysis conducted for the risk-taking subdimension, the model was significant ($R^2 = 0.119$; $F(4, 209) = 7.043$; $p < 0.001$), and sociotechnical blindness was identified as the only significant predictor ($\beta = 0.233$; $t = 2.084$; $p = 0.038$). In the analysis for the innovativeness subdimension, the model was significant ($R^2 = 0.178$; $F(4, 209) = 11.303$; $p < 0.001$), and sociotechnical blindness again emerged as the only significant predictor ($\beta = 0.434$; $t = 4.386$; $p < 0.001$). In the analysis carried out for the proactiveness subdimension, the model was significant ($R^2 = 0.203$; $F(4, 209) = 13.315$; $p < 0.001$), and sociotechnical blindness was found to be a positive, significant, and strong predictor ($\beta = 0.488$; $t = 5.116$; $p < 0.001$). Another striking finding in this analysis is that *the learning subdimension has a negative and significant predictive effect on proactiveness* ($\beta = -0.176$; $t = -2.468$; $p = 0.014$).

Table 7. The Effect of AI Anxiety Subdimensions on IEO Subdimensions (Multiple Regression)

AI Anxiety Subdimension	Risk-Taking β (<i>p</i>)	Innovativeness β (<i>p</i>)	Proactiveness β (<i>p</i>)
Learning	-0.065 (0.375)	-0.033 (0.640)	-0.176 (0.014)
Job Replacement	-0.026 (0.790)	-0.016 (0.866)	0.071 (0.433)
Sociotechnical Blindness	0.233 (0.038)	0.434 (<0.001)	0.488 (<0.001)
AI Configuration	0.121 (0.193)	0.033 (0.706)	0.043 (0.605)
R²	0.119	0.178	0.203
F	7.043	11.303	13.315
p	<0.001	<0.001	<0.001

Note: $p < 0.05$; $p < 0.001$.

4.8. Differences According to Demographic Characteristics

Whether AI anxiety and IEO scores differ according to demographic characteristics was examined through independent samples t-tests and one-way ANOVA analyses. AI anxiety scores were found to differ significantly by gender; the AI anxiety total score of female participants ($M = 2.89$; $SD = 0.87$) was significantly higher than that of male participants ($M = 2.57$; $SD = 0.93$; $t(212) = 2.544$; $p = 0.012$). This difference was observed similarly across all four AI anxiety subdimensions. In comparisons by education level, bachelor's students were found to display significantly higher scores than associate's students on the learning, job replacement, and AI configuration subdimensions. With regard to work experience, participants without work experience reported significantly higher AI anxiety levels than those with work experience on the learning ($t(212) = 2.178$; $p = 0.031$) and sociotechnical blindness ($t(212) = 2.098$; $p = 0.037$) subdimensions.

In terms of individual entrepreneurial orientation, a significant difference was found only for the variable of desire to start one's own business. The IEO total score of participants who wanted to start their own business ($M = 3.67$; $SD = 0.93$) was significantly higher than that of those who didn't ($M = 2.75$; $SD = 0.94$; $t(212) = 6.371$; $p < 0.001$), and this difference was observed across all three subdimensions of IEO. No significant differences were found in IEO scores by gender, education level, university, internship experience, or whether the participant had taken an entrepreneurship course. In line with these results, *hypothesis H2a (the difference in AI anxiety according to demographic characteristics) and hypothesis H2b (the difference in IEO according to demographic characteristics) were partially supported.*

Table 8. Comparison of AI Anxiety Scores by Gender (t-test)

Subdimension	Female (n = 116)	Male (n = 98)	t	p
AI Anxiety Total	2.89 (0.87)	2.57 (0.93)	2.544	0.012
Learning	2.33 (0.99)	1.99 (0.93)	2.612	0.010
Job Replacement	3.28 (1.07)	2.87 (1.03)	2.872	0.005
Sociotechnical Blindness	3.38 (1.11)	2.99 (1.11)	2.548	0.012
AI Configuration	2.93 (1.16)	2.58 (1.17)	2.202	0.029

Note: Values are presented as mean (standard deviation). $p < 0.05$.

Table 9. Comparison of IEO Scores by Desire to Start One's Own Business (t-test)

Subdimension	Yes (n = 157)	No (n = 57)	t	p
IEO Total	3.67 (0.93)	2.75 (0.94)	6.371	<0.001
Risk-Taking	3.53 (1.03)	2.71 (1.09)	4.929	<0.001
Innovativeness	3.64 (1.01)	2.72 (1.01)	5.838	<0.001
Proactiveness	3.84 (0.98)	2.87 (1.02)	6.238	<0.001

Note: Values are presented as mean (standard deviation). $p < 0.001$.

5. Discussion

This study examined the effect of AI anxiety and its four subdimensions on individual entrepreneurial orientation among university students. The findings showed that AI anxiety has a positive and statistically significant effect on IEO. This result is consistent with findings in the literature indicating that anxiety isn't a one-directional variable that suppresses behaviour in every situation, and it provides empirical support for the hybrid theoretical framework of the present study. As the Yerkes-Dodson law and the facilitating–debilitating anxiety distinction of Alpert and Haber (1960) suggest, anxiety can assume an activating function under certain conditions. As Hobfoll's (1989, 2001) Conservation of Resources theory predicts, individuals can engage in proactive initiatives to protect and increase their resources when they perceive themselves as being under threat. The fact that AI anxiety positively predicts IEO indicates that, for university students, the uncertainty AI creates in the labour market transforms into a motivational source that activates entrepreneurial investment rather than passive acceptance.

This finding is consistent in direction with the study of Khalid et al. (2020), conducted on university students in Malaysia, which revealed a positive effect of AI learning on entrepreneurial orientation. There is, however, an important conceptual difference between the two studies. The variable measured by Khalid et al. (2020) was AI learning and knowledge level, while the variable measured in the present study is the negative emotional reaction the individual develops towards AI. Despite this difference, both studies arriving at the same directional result suggests that contact with AI — whether in the form of positive knowledge acquisition or negative anxiety — can activate the entrepreneurial tendencies of university students.

Perhaps the most striking finding of the study is that, among the four subdimensions of AI anxiety, sociotechnical blindness is the only significant predictor of IEO ($\beta = 0.428$; $p < 0.001$). This finding is strikingly parallel to the result of Tuncal and Çeken (2025), conducted on aviation students in Türkiye, which showed that sociotechnical blindness positively predicts perceived employability. Despite the two studies using different dependent variables, the emergence of the same subdimension as a significant predictor suggests that sociotechnical blindness functions among university students not merely as an anxiety dimension but also as a career-oriented motivational trigger. Sociotechnical blindness involves the individual's difficulty in internalising the fact that AI is a system that operates together with humans and social institutions. It also reflects concerns about the potential for technology to spiral out of control, be misused, or produce unforeseen consequences. The mechanism by which such a multilayered threat perception leads individuals to actively seek opportunities, develop innovations, and take risks rather than remain passive is therefore understandable.

The fact that sociotechnical blindness emerges as the only significant predictor of all three IEO subdimensions shows that this dimension systematically activates all sub-components of entrepreneurial behaviour. The β value of sociotechnical blindness on IEO total (0.428) is at levels close to those on proactiveness (0.488) and innovativeness (0.434); the β value on risk-taking (0.233) is comparatively lower but still significant. This pattern reveals that broad-scale sociotechnical threat perceptions have the power to direct individuals particularly towards proactive and innovative behaviours. When evaluated within Hobfoll's (1989, 2001) framework, this finding suggests that sociotechnical blindness constitutes a comprehensive threat to the individual's existing resources (career expectations, professional identity, social trust). Individuals turn towards creating new resources in response to this threat — that is, towards shaping their futures through entrepreneurial behaviours.

Another striking finding of the study is that the learning subdimension has a negative and significant predictive effect on proactiveness ($\beta = -0.176$; $p = 0.014$). Unlike the other subdimensions, anxiety about learning AI technologies *reduces* the individual's tendency to behave proactively. This finding is consistent with that of Tuncal and Çeken (2025), which

showed that learning anxiety negatively predicts perceived employability, and it shows that AI anxiety subdimensions can produce opposite-direction effects on behavioural outcomes. Interpreted within the Yerkes-Dodson framework, this can be explained by the idea that learning anxiety creates a perception of inadequacy regarding the individual's existing skills and serves a “debilitating anxiety” function at the performance level. While abstract, broad-scale, and uncertainty-laden threat perceptions such as sociotechnical blindness activate the individual, concrete, direct, and personally inadequacy-related perceptions such as learning anxiety limit the individual's capacity for proactive initiative.

Demographic analyses showed that AI anxiety differs significantly by gender among university students, with women displaying higher AI anxiety levels than men across all four subdimensions. This pattern is consistent with the finding of Akkaya (2025), whose study on finance and banking students in Türkiye reported that women displayed higher AI anxiety than men. Similarly, Alkhalifah et al. (2024) reported a similar gender effect on health sciences students in Saudi Arabia. The consistent recurrence of this pattern in two different cultural contexts and across different disciplinary samples aligns with the established findings in the literature that women systematically exhibit higher anxiety levels towards new technologies.

In terms of education level, bachelor's students displaying higher AI anxiety scores than associate's students on the learning, job replacement, and AI configuration subdimensions may at first appear counterintuitive. This pattern, however, suggests that bachelor's students develop a more comprehensive awareness of the potential effects of AI on working life as a result of longer academic training, and that this awareness translates into higher anxiety. The fact that students without work experience report higher AI anxiety levels on the learning and sociotechnical blindness subdimensions is consistent with this interpretation. The lack of direct experience of working life leaves individuals alone with uncertainties about how AI operates in the workplace, which leads to more intense anxiety.

In terms of individual entrepreneurial orientation, the most striking result of the demographic analyses is that participants with the desire to start their own business display significantly higher IEO scores across all three subdimensions of the scale. This finding confirms that IEO is a valid behavioural intent indicator and reinforces the relationship predicted between Bolton and Lane's (2012) scale and entrepreneurial intent. The fact that other demographic variables — such as gender, education level, internship experience, and entrepreneurship course — produced no significant differences on IEO indicates that IEO is a relatively stable construct strongly related to entrepreneurial intent.

When the findings of this study are evaluated holistically, AI anxiety among university students is not a passive threat experience. On the contrary, it can assume an activating motivational function, particularly through the sociotechnical blindness dimension. At the same time, the negative effect of learning anxiety on proactiveness shows that AI anxiety subdimensions don't produce uniform effects on behavioural outcomes — they produce effects that differ in both direction and magnitude. This bidirectional pattern provides evidence that the hybrid theoretical framework of the present study — integrating the Yerkes-Dodson law, the facilitating–debilitating anxiety distinction of Alpert and Haber (1960), and Hobfoll's (1989, 2001) Conservation of Resources theory — is empirically valid and offers an explanatory model.

6. Conclusions, Limitations, and Recommendations

6.1. Conclusions

This study aimed to test the effect of AI anxiety and its four subdimensions on individual entrepreneurial orientation among university students in Türkiye. Analyses conducted on 214 university students revealed that AI anxiety has a positive and statistically significant effect on

individual entrepreneurial orientation, explaining approximately 10.9% of the total variance. This result empirically supports the theoretical proposition that anxiety isn't a one-directional variable that suppresses behaviour in every situation; under certain conditions and through certain dimensions, it can transform into a motivational source that activates behaviour.

Among the four subdimensions of AI anxiety, sociotechnical blindness emerged as the only significant positive predictor of IEO ($\beta = 0.428$; $p < 0.001$). The fact that sociotechnical blindness is also the only significant predictor of all three IEO subdimensions (risk-taking, innovativeness, and proactiveness) shows that this dimension systematically activates all components of entrepreneurial behaviour. By contrast, the learning subdimension having a negative and significant predictive effect on proactiveness ($\beta = -0.176$; $p = 0.014$) shows that AI anxiety subdimensions can produce opposite-direction effects on behavioural outcomes. This emphasises the importance of treating AI anxiety as a multilayered concept that needs to be disaggregated.

Demographic analyses showed that AI anxiety differs significantly by gender, education level, and work experience, while individual entrepreneurial orientation differs only by the desire to start one's own business. Notable findings in this context include women displaying higher scores than men across all AI anxiety dimensions, bachelor's students reporting higher anxiety levels than associate's students on certain dimensions, and students without work experience reporting higher AI anxiety levels.

The study makes a theoretical contribution by synthesising three foundational theoretical frameworks — the Yerkes-Dodson law, the facilitating–debilitating anxiety distinction of Alpert and Haber (1960), and Hobfoll's (1989, 2001) Conservation of Resources theory — for the first time in the context of AI anxiety, and by empirically testing this hybrid model. From an empirical standpoint, the study is among the first to systematically demonstrate the effect of AI anxiety on career outcomes in the Turkish context.

6.2. Limitations

This study has several limitations that should be considered in the evaluation of its findings. First, the research was conducted with a cross-sectional design, which doesn't permit direct demonstration of causal relationships. The positive relationship found between AI anxiety and IEO does not allow for definitive inferences regarding the direction of causality between the two constructs in the present design. Second, because data were collected through convenience sampling and largely from students enrolled at Manisa Celal Bayar University, the generalisability of the findings to all university students in Türkiye is limited. Third, the study covers only state university students; foundation (private) university students were not included in the sample. This limits the examination of potential differences across institutional contexts.

Fourth, because data were collected through self-report, biases such as social desirability and common method variance may have affected the results. Fifth, the AI anxiety scale developed by Wang and Wang (2019) was constructed with reference to AI technologies that predated 2019. Yet with the spread of ChatGPT in late 2022, public perceptions of AI underwent a profound transformation. The extent to which the scale captures the new forms of concern brought by the generative AI era (such as threats to creative work or concerns about academic integrity) is a topic that warrants future discussion. Sixth, the explanatory power of the study is comparatively limited. AI anxiety explaining only 10.9% of the variance in IEO, and its subdimensions explaining 19.3% in total, suggests that other variables determining IEO should also be included in the model.

6.3. Recommendations for Future Research

In light of the limitations above, several recommendations can be offered for future research. First, longitudinal and experimental studies are recommended to test the causal direction of the

relationship between AI anxiety and IEO. In particular, studies that experimentally manipulate the level of AI exposure can directly illuminate the causal mechanism between anxiety and entrepreneurial behaviour. Second, future studies forming more representative samples with participants from different universities, different departments, and both state and foundation universities will strengthen the generalisability of the findings.

Third, examining mediating or moderating variables in the relationship between AI anxiety and IEO (such as AI literacy, self-efficacy, career decisiveness, or tolerance of uncertainty) can illuminate the underlying mechanisms in greater detail. The 10.9% explanatory power obtained in the present study clearly demonstrates the importance of including such additional variables in the model. Fourth, the reasons behind the distinctive effect of sociotechnical blindness on university students should be examined more thoroughly through qualitative research methods (in-depth interviews, focus groups). Why this dimension assumes a different motivational function from other AI anxiety subdimensions can be better understood through qualitative data.

Fifth, the development of an updated AI anxiety scale that can capture the new forms of concern brought by the generative AI era is recommended. The areas of use, scope, and societal effects of AI technologies have undergone a profound transformation since 2019, when the existing scale was developed, and reflecting this transformation in the scale items will increase the validity of contemporary research. Sixth, examining the effects of AI anxiety on career outcomes other than IEO (such as career decision-making self-efficacy, occupational adjustment, or job-search behaviour) can reveal the comprehensive effects of AI anxiety in the career domain.

6.4. Practical Implications

The findings of the study offer practical implications in the context of higher education, career counselling, and entrepreneurship policy. First, universities need to systematically include AI literacy training in their curricula. Workshops, certificate programmes, and applied courses that develop students' skills in using AI technologies represent practical intervention areas — particularly for reducing the negative effect of learning anxiety on proactiveness. Positioning such training not as an abstract threat but as a concrete opportunity for skill acquisition can help students transform anxiety into knowledge-based confidence.

Second, career centres and counselling units should be aware of the dual relationship between AI anxiety and entrepreneurship. They should design programmes that support students in transforming this anxiety from a passive obstacle into an active motivational source. The clear positive effect of sociotechnical blindness on IEO shows that broad-scale sociotechnical threat perceptions, when properly channelled, can feed entrepreneurial behaviour. Accordingly, “career in the AI era” themed seminars, entrepreneurship workshops, and mentoring programmes can offer students a valuable support network.

Third, the study's findings on gender differences point to the importance of targeted AI awareness and confidence-building programmes for female students in particular. The systematic display of higher AI anxiety levels by female students suggests that this group may need additional support during the process of engaging with AI technologies.

Finally, in terms of educational policy, entrepreneurship curricula should not be limited to technical knowledge transfer alone. They should also include psychological skills such as anxiety management, strategies for coping with uncertainty, and emotional resource management. The findings of this study show that individual entrepreneurial orientation isn't solely a cognitive or personality-based construct. It takes shape in interaction with the individual's emotional states — particularly with negative emotions such as anxiety. Designing entrepreneurship education to also cover the components of emotional literacy and psychological resilience will therefore make an important contribution to the formation of future entrepreneurial generations.

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Ethical Approval

This study was approved by the Ethics Committee for Social and Humanities Sciences of Manisa Celal Bayar University at its meeting dated 26 February 2026 (number 2026/03), under decision number 19. All participants were informed about the aim of the research, the principle of voluntary participation, the assurance of anonymity, and their right to withdraw at any time. Informed consent was obtained from all participants prior to data collection.

Author Contributions

A.B.P. (Pala) and H.A. (Aktaş) jointly developed the conception and design of the study, the methodology, and the theoretical framework. A.B.P. was responsible for the literature review, the data collection, the statistical analyses, and the drafting of the manuscript. H.A. supervised the research and conducted the critical revision of the manuscript. Both authors read and approved the final manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest with regard to the publication of this manuscript.

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