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Research Article

Global regulatory trends in gamification and practical pathways for digital fairness

Hayri Baytan Ozmen[*a]

Faculty of Engineering and Natural Sciences, Uşak University, Uşak, Türkiye

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Abstract

Gamification has evolved from a simple user engagement strategy into a complex behavioral architecture capable of exploiting cognitive biases. The aggressive expansion of the global gamification market has precipitated a rise in manipulative digital interfaces, commonly known as dark patterns, across finance, labor, and youth oriented digital ecosystems. This article provides a comprehensive global regulatory analysis of the recent legal and ethical transformations surrounding digital gamification between. It contrasts the European Union's precautionary and ex-ante regulatory frameworks, specifically the Digital Services Act and the proposed Digital Fairness Act, with the decentralized and ex-post enforcement model utilized in the United States. Furthermore, this study evaluates sector specific legal interventions addressing digital engagement practices in retail investing, algorithmic workplace management, and gamified fraud targeting minors. To bridge the gap between emerging regulatory mandates and practical software engineering, this article introduces a new Fairness by Design lifecycle model. By synthesizing the ETHIC framework and IEEE 7000 series standards into the conventional Software Development Life Cycle, the research provides an operational blueprint for embedding algorithmic accountability directly into the gamification development process. The study concludes that sustainable market leadership necessitates a paradigm shift from engagement centric metrics toward proactive ethical engineering.

1. Introduction

Gamification, defined as the integration of game design elements and mechanics into non game contexts, has undergone a profound transformation over the last two decades [1]. Initially conceptualized as a neutral and highly effective digital marketing and user engagement strategy, it has progressively evolved into a highly sophisticated form of behavioral architecture. This transition is characterized by a shift from simple reward systems to complex algorithmic designs that continuously monitor and steer user behavior [2, 3]. As platforms increasingly optimize for user retention and habitual engagement, global regulatory bodies and academic scholars have begun to heavily examine these systems [4, 5]. Modern gamification is no longer merely a tool for enhancing user interfaces but is increasingly recognized as a mechanism capable of exploiting cognitive biases and psychological vulnerabilities [6].

The contemporary landscape of behavioral design is defined by its dual nature, presenting both significant societal benefits and profound ethical risks. On the constructive end of the spectrum, gamification has demonstrated remarkable efficacy in sectors such as healthcare and education. For instance, the integration of game mechanics in patient care delivery and wellness programs has been shown to boost patient engagement and foster long term healthy behavior changes, with some

*Corresponding author: baytan.ozmen@usak.edu.tr
[a]orcid.org/0000-0001-6750-8632
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implementations yielding up to a 50% increase in active participation [7, 8]. However, even within these traditionally constructive domains, the deployment of gamified learning in immersive environments and healthcare delivery necessitates rigorous ethical boundaries [7, 9]. Without proactive design frameworks, systems originally intended for user empowerment can easily drift toward exploitative behavioral tracking, underscoring the universal need for proactive fairness methodologies regardless of the sector's inherent utility.

The exploitative end of this spectrum is increasingly prevalent in digital ecosystems optimized for hyper consumption and risk taking. In retail financial markets, digital engagement practices (DEPs) such as confetti animations for completed trades, hidden fees, and deceptive urgency have dangerously blurred the boundaries between investing, gaming, and gambling [10].

Fig. 1 illustrates the conceptual continuum of behavioral design. The left side of the spectrum represents constructive engagement techniques, such as educational milestones and health tracking, which rely on intrinsic motivation and transparent rewards to empower the user and drive positive health outcomes [8]. Moving toward the right, the design mechanisms become increasingly manipulative, ultimately culminating in "dark patterns" such as infinite scrolling, confirmshaming, and fake urgency timers. These exploitative architectures are engineered to bypass rational decision making and prioritize corporate metrics over user well-being [6].

Fig. 1. The Gamification spectrum from constructive engagement to dark patterns

The urgency to regulate these digital environments is inextricably linked to the massive economic expansion of the gamification industry. As digital platforms across all sectors adopt these behavioral techniques, the financial stakes have grown exponentially. In 2025, the global gamification market reached a valuation of $26.91 billion. Driven by the widespread integration of gamified finance applications, workplace algorithmic management tools, and immersive e commerce platforms, the market is projected to experience aggressive growth. Forecasts indicate a compound annual growth rate (CAGR) of 28%, propelling the market volume to an estimated $92.37 billion by the year 2030 [11].

Given the rapid market expansion and the increasing sophistication of behavioral manipulation techniques, a critical examination of the existing legal landscape is required. The primary objective of this article is to analyze the current state of global digital regulations concerning gamification. This research will systematically map the legal boundaries of dark patterns, evaluate sector specific risks across finance, labor, and child protection, and explore the future of ethical compliance frameworks. By comparing diverse regulatory strategies, specifically the approaches adopted by the European Union and the United States, this article aims to identify the necessary legal and ethical transformations required to ensure sustainable and fair digital growth.

Furthermore, to bridge the gap between abstract regulatory mandates and practical software engineering, this article introduces a new operational model. By synthesizing established ethical guidelines, namely the IEEE 7000 [12] series and the ETHIC framework [6], into the standard Software Development Life Cycle (SDLC), this research proposes a pragmatic Fairness by Design lifecycle model. This proposed architecture is designed to embed algorithmic accountability directly into the gamification development process, offering a structural blueprint for the industry.

2. The Conceptual Evolution of Gamification

Over the past decade, the concept of gamification has undergone a profound conceptual and functional transformation within academic literature. Early research primarily conceptualized gamification as a constructive pedagogical and motivational tool designed to enhance user engagement in structured environments. Academic studies consistently documented its efficacy, illustrating how gamified interventions could enhance intrinsic motivation in complex subjects, such as architectural heritage education in the metaverse and immersive healthcare training [9, 13]. Meta-analytic reviews during this period confirmed that gamified reward systems yielded moderate but statistically significant positive effects on short-term behavioral change, particularly among adult learners [14, 15]

However, as digital ecosystems became increasingly commercialized and platform economies pivoted toward data-driven business models, a radical shift occurred in academic discourse. Contemporary research no longer views gamification merely as a neutral motivational tool, but rather as a strategic behavioral architecture capable of shaping consumption habits and driving platform-scale growth [16]. This intersection of human-computer interaction (HCI), behavioral economics, and law has led scholars to heavily dissect the ethical boundaries of digital nudging. When optimized to maximize corporate metrics rather than user utility, these hyper-personalized interventions systematically exploit human psychological vulnerabilities [17, 18]. This exploitative practice is increasingly distinguished from ethical nudging and is referred to in the literature as "sludging" [19].

2.1. Exploitation of Cognitive Biases and Heuristics

This transition toward behavioral architecture is deeply rooted in behavioral economics and cognitive psychology. Academic literature emphasizes that the traditional rational choice theory, which assumes market actors possess perfect knowledge and act with deliberate rationality, fails to accurately model consumer behavior in digital environments characterized by severe information asymmetry [19]. Instead, relying on the dual-process theory of cognition detailed by Kahneman [20], modern platform interfaces are explicitly engineered to exploit fast, automatic, and emotional System 1 decision-making processes, deliberately bypassing the analytical and rational System 2. The effectiveness of this behavioral manipulation is empirically validated; for instance, large-scale randomized controlled experiments demonstrate that dark patterns effectively disable rational deliberation, drastically increasing user compliance against their own economic interests [21]. The academic consensus is that these manipulative gamification mechanisms do not aim to alter consumer preferences, but rather to exploit specific cognitive biases to coerce users into taking actions fundamentally inconsistent with their actual intentions.

To fully understand the mechanics of these behavioral architectures, it is necessary to ground them in foundational motivational theories. The transition from constructive gamification to manipulative design can be mapped through Self-Determination Theory (SDT) [22], which emphasizes the innate human psychological needs for autonomy, competence, and relatedness. While ethical gamification supports intrinsic motivation and user autonomy, dark patterns systematically undermine it by deploying coercive extrinsic drivers. The mechanical efficacy of these drivers is best understood through the Fogg Behavior Model [23], which suggests that a target behavior occurs when motivation, ability, and a prompt converge simultaneously. Exploitative digital interfaces weaponize this equation by artificially inflating motivation (e.g., through engineered scarcity), reducing the cognitive ability required to comply (e.g., via frictionless default biases), and deploying aggressive digital prompts. This deliberate subversion of human autonomy forms the precise psychological basis for why contemporary legal frameworks, such as the proposed Digital Fairness Act, are shifting to categorize these designs as actionable impairments to consumer free will [24].

Research highlights several primary cognitive biases systematically exploited by interface designers:

- Default Bias and the Status Quo Effect: Platforms exploit the human tendency to maintain the current state by utilizing pre-checked boxes and arduous cancellation models. This artificially increases the cognitive load required to make an independent choice, ensuring passive acceptance [25].

- Scarcity Bias and Fear of Missing Out (FOMO): Artificial countdown timers and fake "limited stock" warnings prevent rational cost-benefit analysis, triggering impulsive purchasing behaviors by coercing users to assign higher value to perceptually rare items [25].
- Loss Aversion and the Sunk Cost Fallacy: Because human psychology perceives potential losses more acutely than equivalent gains, gamified systems leverage digital streaks to threaten users with the loss of their invested time, virtually mandating continuous engagement [21].
- Framing Effect and Social Proof: Interfaces utilize manipulative language (confirm shaming) or exaggerated notifications of other users' actions to trigger herd mentality, weaponizing social norms to weaken independent decision-making [26].

2.2. Ontological Development of Dark Patterns and Harm Measurement

The academic investigation into the extreme manifestation of these architectures, commonly termed "dark patterns", developed in distinct methodological waves. Initial research by Bösch et al. and Gray et al. focused on defining the phenomenon and categorizing basic theoretical typologies [27, 28]. A subsequent wave of empirical research, highlighted by a landmark study from researchers at Princeton and the University of Chicago utilizing semi-automated scanning across 11,000 popular e-commerce websites, proved the systemic prevalence of these manipulative designs [29].

To resolve the resulting conceptual fragmentation across disciplines, recent literature has focused heavily on ontological harmonization. Researchers have proposed standardized, multi-level ontologies, such as a comprehensive framework encompassing 64 distinct manipulative design types, synthesizing disparate taxonomies to analyze temporal manipulation across continuous interactions [30].

The documented impact of these designs extends far beyond financial detriment to encompass severe intangible harms, including privacy violations, emotional distress, attention deficits, and a fundamental loss of consumer autonomy [31]. A recent systematic review analyzing platforms operating in the EU and UK markets (2021–2025) provided critical empirical evidence regarding consumer trust. The study demonstrated that 83.3% of the analyzed brands utilized countdown timers and 66.7% used fake scarcity claims. While these manipulative pressure nudges may temporarily increase conversion rates by 5% to 30%, they dramatically erode long-term consumer trust and sustainable brand affinity [32]. This undeniable empirical evidence of structural and psychological harm serves as the theoretical foundation for the global regulatory shift toward algorithmic accountability.

2.3. Legal Review of Behavioral Architecture

Parallel to empirical human-computer interaction (HCI) studies, legal scholars have critically evaluated the regulatory frameworks attempting to govern behavioral architecture. A primary academic critique of traditional European consumer law, such as the Unfair Commercial Practices Directive (UCPD), is its reliance on the average consumer benchmark [33]. Scholars argue this standard is obsolete in the digital age, as it fails to account for the dynamic cognitive vulnerabilities exploited by algorithmic hyper-personalization. Furthermore, while the Digital Services Act (DSA) introduces explicit prohibitions against interfaces that deceive or manipulate users, academic commentators warn that the fragmented interplay between the DSA, the General Data Protection Regulation (GDPR), and existing consumer directives creates profound legal inconsistencies and risks severe under-enforcement [31].

Consequently, the proposed Digital Fairness Act (DFA) has become a focal point of intense academic debate. While consumer protection advocates and civil society researchers argue that a horizontal instrument is necessary to mandate "fairness by design" and address systemic autonomy violations, other scholars caution against regulatory overreach. Researchers argue that layering the DFA over the existing, dense regulatory framework risks creating overlapping obligations, generating legal uncertainty, and imposing disproportionate red tape on innovation without necessarily improving enforcement outcomes [34]. To bridge this gap, contemporary academic methodologies, such as the temporal analysis of dark patterns, are being proposed to provide regulators with rigorous frameworks to capture the evolving, long-term impact of manipulative designs on user autonomy [30].

3. The Current State of Gamification Regulation Tackling Dark Patterns

Dark patterns are designed to coerce consumers into making decisions that disproportionately benefit the platform, such as impulsive spending, unintended data sharing, or prolonged platform engagement [35]. Common manifestations include fake urgency through artificial countdown timers, infinite scrolling mechanisms that eliminate natural stopping cues, and roach motel designs that make subscribing effortless but canceling deliberately arduous.

To systematically address these manipulative designs, it is necessary to categorize them based on their psychological mechanisms and the specific legal frameworks attempting to govern them. Table 1 provides a taxonomy of prevalent dark patterns and maps them to the European Union legal instruments currently deployed to mitigate their effects. This taxonomy synthesizes definitions from the European Parliamentary Research Service (2025) [35] and BEUC (2025) [24], illustrating the fragmented nature of current digital regulations where different design elements fall under distinct legal directives.

Table 1. Taxonomy of dark patterns and applicable EU legal frameworks

Dark Pattern Typology	Psychological Trigger & Behavioral Effect	Applicable EU Legal Framework	Regulatory Countermeasure
Fake Urgency & Scarcity	Exploits the fear of missing out (FOMO) to force rushed purchasing decisions (e.g., fake countdown timers).	Unfair Commercial Practices Directive (UCPD)	Classified as a misleading commercial practice requiring immediate enforcement against deceptive sales tactics.
Infinite Scrolling & Auto-play	Eliminates natural stopping cues, creating a frictionless loop that maximizes time spent on platform.	Digital Services Act (DSA)	Addressed under systemic risks to user well-being and mental health (Recital 67), prompting structural design changes.
Confirm shaming & Guilt Nudges	Uses emotive language to make the user feel guilty or foolish for declining an offer.	Upcoming Digital Fairness Act (DFA)	Targeted for elimination under proposed "fairness by design" mandates that require neutral choice architectures.
Privacy Zuckering & Forced Consent	Confuses users with complex settings to trick them into sharing more personal data than intended.	General Data Protection Regulation (GDPR)	Violates the principle of informed, freely given, and unambiguous consent, rendering the data collection unlawful.

The European Union has adopted an aggressive, ex-ante regulatory posture to combat these practices. The enactment of the Digital Services Act (DSA) represents a paradigm shift, as it expressly prohibits manipulative design techniques that materially distort or impair the ability of consumers to make autonomous and informed choices. High-profile enforcement actions have already commenced under this framework. For instance, the European Commission recently launched a formal probe into the e-commerce giant Shein to investigate whether its gamified reward systems and addictive design features violate the DSA [36]. Similarly, the Commission initiated proceedings against TikTok, arguing that its core design features, including infinite scrolling and algorithmic recommendations, are inherently addictive and fail to protect minors [37, 38].

Despite these advancements, the European framework suffers from significant regulatory fragmentation. Practices already covered by the Unfair Commercial Practices Directive (UCPD) or the General Data Protection Regulation (GDPR) are explicitly excluded from the scope of the DSA.

This exclusion creates legal ambiguity regarding which authority has jurisdiction over specific interface designs [35]. To rectify this, European consumer organizations are heavily advocating for the Digital Fairness Act, which aims to harmonize these rules and mandate a horizontal "fairness by design" principle across all digital products [24].

Conversely, the regulatory environment in the United States is characterized by a fragmented, ex-post approach. The US currently lacks a comprehensive federal statute dedicated to governing gamified interfaces or algorithmic behavioral manipulation. Instead, federal enforcement relies heavily on Section 5 of the Federal Trade Commission (FTC) Act, which prohibits unfair or deceptive acts or practices. The FTC has actively pursued enforcement actions against companies utilizing dark patterns, particularly those affecting subscription cancellations and data privacy, in collaboration with international networks like the International Consumer Protection and Enforcement Network [39].

However, broader systemic regulation in the US has faced severe friction. Attempts to regulate gamification in specific sectors have been met with intense resistance. For example, the Securities and Exchange Commission (SEC) proposed a rule in 2023 to neutralize conflicts of interest in predictive data analytics and digital engagement practices on trading platforms. Following unprecedented industry backlash arguing that the rules would stifle technological innovation, the SEC formally withdrew the proposal in late 2025 [10]. Consequently, the burden of regulation has largely shifted to state-level litigation, such as the widely cited enforcement action by Massachusetts regulators against Robinhood for breaching fiduciary duties through the use of celebratory confetti animations and gamified trading prompts [40].

This reliance on ex-post litigation reached a historic milestone in March 2026, when a Los Angeles jury found Meta and YouTube liable for deliberately engineering addictive design features that caused severe mental health harm to a young user. In this landmark bellwether trial, the plaintiffs successfully bypassed traditional content moderation shields (such as Section 230 of the Communications Decency Act) by arguing a negligence-based product liability theory [41]. The jury determined that the platforms' foundational informational architecture, specifically features like infinite scrolling, autoplay mechanisms, and unpredictable reward loops, functioned as defective and dangerous product designs [42]. The resulting $6 million damage award establishes a critical legal precedent that algorithmic engagement mechanics are subject to strict product safety obligations, fundamentally challenging how tech platforms construct their user interfaces and reinforcing the tangible legal risks of unregulated gamification.

To illustrate fundamental differences in regulatory philosophy, scope, and enforcement mechanisms, Table 2 provides a comparative analysis of the European Union's precautionary framework versus the United States' market-based model.

The divergence between the EU and the US underscores a fundamental philosophical debate in digital regulation. The European model prioritizes consumer protection and mental well-being through stringent, harmonized oversight, whereas the American model heavily weights market freedom, corporate innovation, and subsequent legal remedies. As behavioral design technologies become increasingly sophisticated, bridging this regulatory divide will be essential for multinational corporations operating in the global digital economy.

Table 2. Comparative analysis of EU vs. US approaches to digital fairness

Regulatory Dimension	European Union (Precautionary / Harmonized)	United States (Market-Based / Decentralized)
Primary Legislation	Digital Services Act (DSA), Unfair Commercial Practices Directive (UCPD), Digital Fairness Act (Proposed).	Federal Trade Commission (FTC) Act Section 5, Sector-specific agency rules (e.g., SEC), State-level consumer protection laws.
Enforcement Mechanism	Ex-ante systemic regulation. Platforms must conduct risk assessments and design compliant interfaces prior to deployment.	Ex-post litigation. Enforcement relies heavily on retroactive lawsuits, settlements, and agency actions after harm has occurred.
Scope of Definition	Broad focus on systemic risk, behavioral manipulation, and the psychological impact of design architectures.	Narrow focus on specific deceptive, fraudulent, or unfair commercial practices that cause direct consumer injury.

While the transatlantic divergence between the EU and the US represents the primary philosophical fault line in digital regulation, a comprehensive global analysis necessitates acknowledging alternative, non-Western frameworks. In Asia, China has deployed a highly stringent, state-centric approach to algorithmic governance. The 2022 Internet Information Service Algorithmic Recommendation Management Provisions represent one of the most direct legal interventions against exploitative behavioral architectures globally, explicitly prohibiting algorithmic models that induce user addiction, excessive consumption, or violate the physical and mental health of minors [43].

Simultaneously, emerging digital rights frameworks in Latin America are actively adapting European precautionary principles to local contexts. The enforcement of Brazil's General Data Protection Law (LGPD), coupled with its advanced legislative proposals for artificial intelligence (Bill 2338/2023), highlights a growing regional movement to codify algorithmic transparency and penalize manipulative data practices outside the Western hemisphere [44, 45].

This increasing global fragmentation of digital law reinforces the fundamental premise of this study. As multinational platforms are forced to navigate a patchwork of contradictory legal requirements, from European ex-ante mandates to strict Chinese algorithmic prohibitions, etroactive legal compliance is no longer viable. Integrating universal ethical standards, such as the IEEE 7000 and ETHIC frameworks, directly into the foundational software architecture ensures a baseline of algorithmic accountability capable of withstanding diverse global scrutiny.

4. Sectoral Trends and Legal Interventions

The theoretical risks posed by deceptive behavioral design materialize differently across various sectors of the digital economy. Between 2023 and 2026, regulatory authorities have shifted from general consumer protection advisories to targeted, sector specific interventions. This period has seen an unprecedented focus on financial markets, workplace algorithmic management, and child protection ecosystems, as the distinct harms of gamification in each domain have become quantitatively measurable and legally actionable.

To provide a comprehensive overview of how these risks manifest across different industries, Table 3 outlines a typology of sector specific gamification risks, detailing the prevalent mechanics, targeted vulnerabilities, and documented harms. This matrix synthesizes sector specific risks identified in regulatory actions by the Financial Conduct Authority (2022) [46], the US Department of Labor (2024) [47], and the Federal Trade Commission (2024) [48].

Table 3. Typology of sector specific gamification risks

Sector	Prevalent Gamified Mechanic	Psychological Trigger	Target Vulnerability	Documented Harm
Finance and Investing	Confetti animations, push notifications, prize draws	Dopamine driven reward seeking, FOMO	Inexperienced retail investors (specifically ages 18 to 34)	Impulsive trading, portfolio risk escalation, financial losses
HR and Workplace	Algorithmic performance leaderboards, biometric tracking	Social competition, fear of penalty	Warehouse logistics workers, job applicants	Algorithmic fatigue, severe ergonomic injuries, hiring discrimination
Youth and Gaming	Loot boxes, infinite scroll, task based rewards	Variable ratio reinforcement, social validation	Minors, young adults seeking employment	Grooming by criminal networks, mental health decline, financial fraud

4.1. Financial Markets and Investment Platforms

Nowhere is the intersection of gamification and legal liability more pronounced than in the retail financial sector. Digital Engagement Practices (DEPs) have aggressively blurred the lines between gaming, gambling, and investing. While these applications ostensibly democratize finance by making platforms intuitive and engaging, they frequently encourage excessive trading and risk taking [10].

Table 4. Quantitative impact of Digital Engagement Practices (DEPs) on investor behavior

Digital Engagement Practice (DEP)	Behavioral Effect on Trading Activity	Demographic Vulnerability
Push Notifications	Increased trading frequency by 11%	Elevated portfolio risk, most severe in the 18 to 34 age bracket
Prize Draws and Lotteries	Increased trading frequency by 12%	Disproportionately affected users with low financial literacy
Celebratory Animations	Normalized high frequency trading via positive reinforcement	Reduced perception of financial risk and loss

The UK Financial Conduct Authority (FCA) has provided critical empirical evidence demonstrating how specific design architectures actively harm consumers. In a comprehensive study of trading app design, the FCA found that gamified elements significantly alter consumer behavior, pushing users toward riskier financial decisions regardless of their underlying financial literacy. Table 4 details the quantitative impact of these specific DEPs. Data is derived from the experimental research published by the Financial Conduct Authority (2024) regarding problem behaviors linked to trading app design [46].

In response to these systemic risks, the European Union has taken decisive legislative action. The EU Retail Investment Strategy (RIS) has proposed a comprehensive ban on "payment for order flow" (PFOF) starting in 2026. This regulatory intervention is explicitly designed to dismantle the economic incentive structures that encourage brokers to gamify their platforms to maximize trading volume at the expense of investor welfare[49, 50].

4.2. Algorithmic Management in the Workplace

The deployment of gamification within enterprise and labor environments has sparked intense legal scrutiny, particularly concerning algorithmic management and surveillance. Rather than fostering engagement, gamification in logistics and warehousing is increasingly utilized to enforce rigorous performance metrics, a practice researchers have described as weaponizing the workplace [51].

The relentless pace dictated by algorithmic leaderboards and automated task tracking has led to severe and measurable physical consequences for workers. Reports indicate that facilities utilizing heavily gamified, algorithmic pacing systems frequently record musculoskeletal injury rates significantly higher than industry averages, driven by software architectures that penalize natural pauses in movement [51]. In response to these quantifiable ergonomic hazards, the US Occupational Safety and Health Administration (OSHA) intervened directly, citing the direct correlation between automated productivity tracking and worker injury. In a historic settlement in late 2024, the US Department of Labor mandated that Amazon implement corporate wide ergonomic measures across its facilities nationwide. This agreement forces structural redesigns, job rotations, and the implementation of ergonomic equipment, effectively legally capping the physical toll exacted by algorithmic productivity tracking [47].

Concurrently, the integration of gamified AI assessments in the hiring process has introduced profound legal liabilities regarding employment discrimination. While vendors market these neuroscience based games as tools to reduce bias, they present severe risks under employment law. These tools often rely on opaque algorithms that measure subjective traits, raising significant concerns regarding scientific validity, indirect discrimination against neurodivergent candidates, and the unauthorized collection of biometric data [52].

4.3. Child Protection and Gamified Scams

Vulnerable demographics, particularly minors and young job seekers, face highly targeted risks from malicious actors exploiting gamified ecosystems. A highly concerning trend identified by the Federal Trade Commission (FTC) is the exponential rise of "task scams" (Fig. 2). These fraudulent schemes disguise themselves as gamified remote jobs, coercing victims into paying continuous fees to unlock the next level or task to access promised earnings.

Fig. 2 highlights the explosive growth of gamified job fraud. According to the FTC Consumer Sentinel Network, task scams grew from accounting for just 0.6 percent of job scams in 2021 to a staggering 38.8 percent in the first half of 2024. In the first six months of 2024 alone, reported financial losses to these gamified frauds eclipsed $220 million, underscoring a massive regulatory blind spot in digital consumer protection [48].

Beyond financial fraud, the structural architecture of multiplayer gaming ecosystems is being actively exploited by violent organizations and hybrid criminal networks. UNICEF research indicates that these malign actors leverage the social features and gamified communication channels of popular games to propagandize, groom, and recruit children [53].

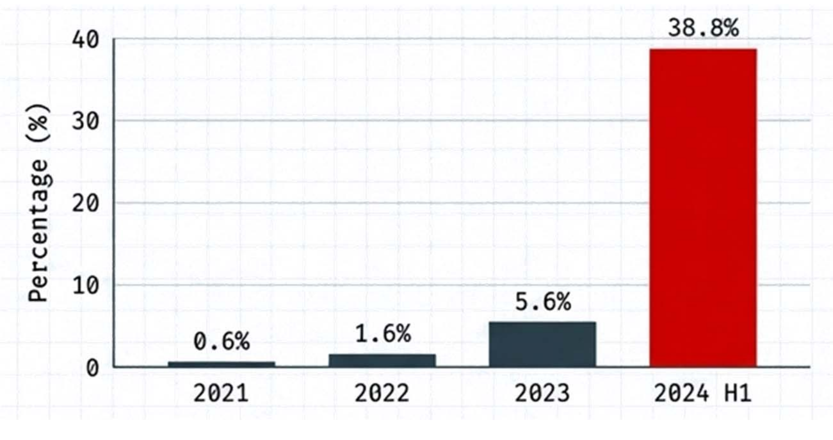

Fig. 2. Escalation of financial losses from gamified task scams (2021 to 2024).

To combat this, a global shift towards stringent digital regulation for children has emerged. The UK Online Safety Act has established a rigorous "duty of care" for platforms, moving away from voluntary self-regulation. Across the EU, US, and Australia, new legislative frameworks are mandating sophisticated age verification protocols and prioritizing "safety by design" principles, forcing platforms to disable inherently risky gamified features by default for underage users [54].

5. Future Perspectives Algorithmic Accountability and Fairness by Design

The escalating legal interventions observed between 2023 and 2026 signal a permanent paradigm shift in the digital economy. The era of evaluating platform success exclusively through engagement centric metrics, such as "Time Spent on App" or "Daily Active Users," is rapidly closing. In its place, regulatory bodies are establishing legal compliance models centered on user well-being, data minimization, and algorithmic accountability. This transition requires technology developers to abandon retroactive compliance strategies and instead embed ethical considerations directly into the foundational architecture of their digital products.

To contextualize the speed and scale of this regulatory evolution, Fig. 3 illustrates the convergence of key legislative and enforcement milestones that have reshaped the global compliance landscape.

This chronological mapping demonstrates the rapid acceleration of digital regulation. Key milestones include the full enforcement of the EU Digital Services Act (DSA) and subsequent probes into TikTok and Shein in early 2024 and 2026 respectively. In the United States, the timeline highlights the FTC's coordinated global enforcement actions against deceptive subscription models in 2024, alongside the historic OSHA settlement with Amazon regarding algorithmic workplace management. Furthermore, the timeline maps the proliferation of child safety mandates, culminating in the enforcement of the UK Online Safety Act and various state level age appropriate design codes across the US by 2025 [37, 47, 54].

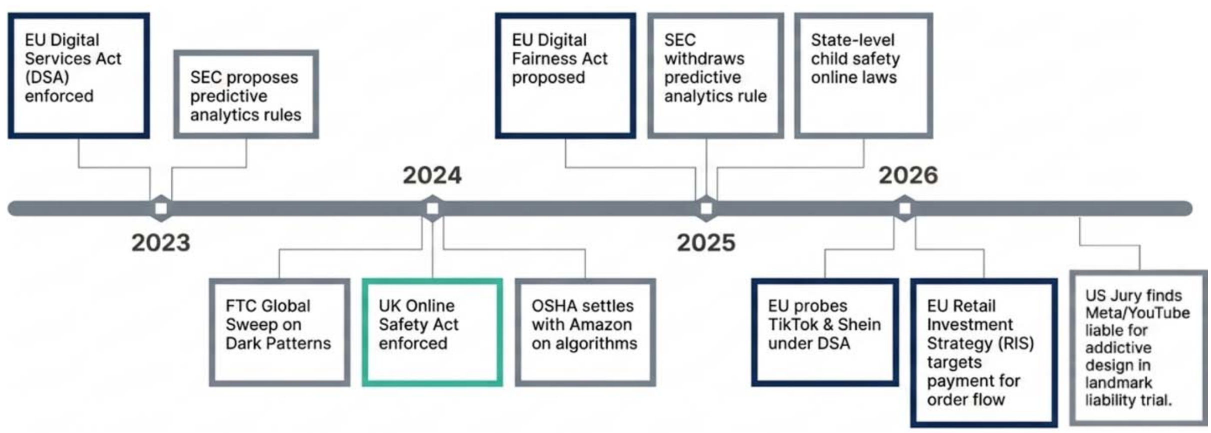

Fig. 3 Timeline of global digital regulation advancements (2023 to 2026).

A central pillar of this emerging regulatory framework is the transition from ex-post enforcement to ex-ante structural mandates. The most significant development in this regard is the European Union's proposed Digital Fairness Act (DFA). The DFA is explicitly designed to harmonize existing consumer protection directives and close the regulatory loopholes that currently allow manipulative gamification to thrive. Most notably, the DFA seeks to establish "fairness by design" as a mandatory legal obligation rather than a voluntary industry best practice. Under this framework, platform operators will be strictly prohibited from utilizing specific behavioral architectures, including infinite scroll, frictionless auto play mechanisms, and addictive variable ratio reward systems, without providing users with immediate and accessible opt out mechanisms [24, 35].

To operationalize these stringent legal requirements, the technology sector is increasingly relying on standardized engineering frameworks. Prominent among these are the IEEE 7000 and 7010 standards for Ethically Aligned Design (EAD). The IEEE EAD paradigm provides a rigorous methodology for "Value based Engineering," shifting the burden of ethical compliance from legal departments directly to software engineers and user interface designers. By requiring comprehensive risk assessments during the ideation phase, these standards ensure that principles such as human well-being, transparency, and algorithmic accountability are encoded directly into the core architecture of AI systems and gamified platforms before a single line of code is deployed [12].

For practical application in corporate compliance and product development, frameworks that bridge the gap between high level legal mandates and daily software development are critical. The "ETHIC Framework" has emerged as a highly recommended structural guide in this domain. Standing for Empowerment, Transparency, Helpfulness, Integrity, and Control, the ETHIC framework provides a systematic checklist for evaluating gamified features. It forces developers to ask whether a reward system empowers the user to achieve their own goals or merely exploits a psychological vulnerability to maximize corporate metrics [5, 6].

While the IEEE 7000 series and the ETHIC framework offer robust theoretical foundations for ethical engineering, a significant gap remains in translating these high level mandates into daily operational development routines. To address this, a primary contribution of this article is the proposition of a novel and integrated Fairness by Design lifecycle model, illustrated in Fig. 4. This model represents an original synthesis that directly maps the five principles of the ETHIC framework and the Value Based Engineering methodologies of the IEEE 7000 standard onto the traditional Software Development Life Cycle (SDLC) [6, 12].

This synthesis specifically targets the 'translation gap' prevalent in digital ethics, wherein abstract ethical principles frequently fail to permeate standard engineering practices [55]. In isolation, the existing frameworks are structurally insufficient for product development; the IEEE 7000 series is methodologically robust but highly theoretical, while the ETHIC framework functions as a static heuristic checklist. Neither provides a temporal execution strategy. The conceptual relationship within the proposed synthesis is synergistic: the ETHIC framework establishes what behavioral heuristics must be evaluated, the IEEE 7000 standard provides the methodological rigor of how to assess these values, and the SDLC establishes when these specific interventions must occur within the temporal lifecycle of software production. By interlocking these elements, the proposed model fills the critical operational gap between ex-ante legal compliance and the daily deployment sprints of software engineers.

Rather than treating ethical compliance as a post launch legal review, this proposed architecture embeds specific and actionable ethical injection points into every phase of production. For instance, during the initial Ideation and Prototyping phase, the model mandates predictive ethical risk assessments. During Deployment, it enforces strict dark pattern screening to guarantee user agency and informed consent. Finally, the Post Launch Monitoring phase establishes a continuous feedback loop utilizing data analytics to detect unintended behavioral harms, such as algorithmic fatigue or impulsive financial behavior, which then trigger mandatory iterative redesigns. By operationalizing these diverse theoretical frameworks into a cohesive engineering pipeline, this model provides organizations with a practical blueprint to systematically transition from reactive compliance to proactive algorithmic accountability.

While the proposed Fairness by Design lifecycle model provides a robust theoretical blueprint derived from established ethical standards, it is important to acknowledge that this integrated architecture has not yet been subjected to empirical testing. Because it represents a novel synthesis of the ETHIC framework and IEEE 7000 standards directly into the SDLC, its operational efficacy remains conceptual. Future research must prioritize longitudinal case studies within active software development environments to empirically validate this model.

As these regulatory and technical frameworks mature, the legal liabilities associated with manipulative gamification will only increase. Future market leaders will not be defined by their ability to hijack human attention, but by their capacity to integrate transparent, user centric ethical designs into their core operational processes.

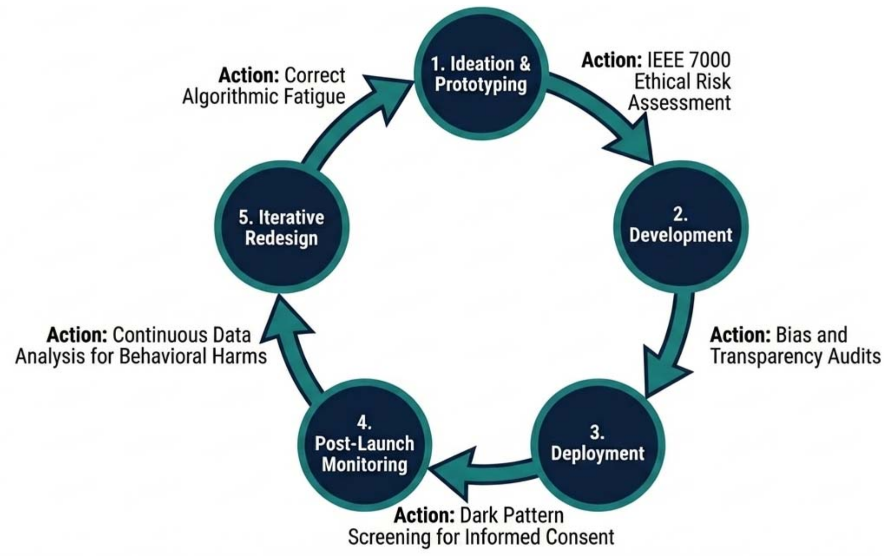

Fig. 4. Operationalizing the fairness by design lifecycle.

6. Conclusion

The recent period starting by 2023 marks a pivotal era in the digital economy, characterized by the legal and ethical transformation of gamification. What was once conceptualized as a benign strategy for maximizing user engagement has definitively evolved into a highly scrutinized form of behavioral architecture. With the global gamification market projected to exceed $92 billion by 2030, the economic incentives to deploy persuasive technologies have never been higher. Consequently, the proliferation of manipulative interfaces, commonly known as dark patterns, has necessitated urgent and comprehensive regulatory interventions across multiple sectors. The findings of this analysis underscore that the unregulated optimization of human attention is no longer legally sustainable, highlighting a critical global shift toward algorithmic accountability and user centric digital fairness.

- The regulatory landscape is currently defined by a significant philosophical divergence between major global markets. The European Union is pioneering a precautionary, ex-ante approach, utilizing instruments like the Digital Services Act to mandate systemic risk assessments and mitigate manipulative choice architectures before they cause widespread harm.
- Building upon these initial European frameworks, the impending Digital Fairness Act represents a paradigm shift from fragmented consumer protection directives to a harmonized, horizontal mandate. This legislation will legally obligate platforms to integrate "fairness by design" principles, effectively outlawing inherently addictive features such as infinite scrolling and artificial urgency.
- Conversely, the regulatory environment in the United States remains highly decentralized and market driven. In the absence of comprehensive federal legislation, accountability relies heavily on ex-post enforcement actions spearheaded by the Federal Trade Commission and state level regulators, targeting specific instances of consumer fraud and deceptive subscription models.
- In the financial sector, digital engagement practices have dangerously conflated investing with gambling, particularly impacting novice and younger retail investors. Empirical evidence demonstrating the correlation between celebratory animations, push notifications, and escalated portfolio risk has catalyzed stringent countermeasures, notably the European Union's aggressive move to ban payment for order flow.
- The deployment of gamified algorithmic management within labor environments has transitioned from an operational efficiency tool to a profound legal liability. Escalating physical injury rates and algorithmic fatigue have prompted direct intervention from

occupational safety authorities, establishing legal precedents that cap the physical toll of automated productivity tracking.

- The exponential rise in gamified task scams and the exploitation of multiplayer ecosystems by illicit networks have forced a global reevaluation of digital child protection. The legislative momentum has permanently shifted from voluntary corporate self-regulation to strict statutory duties of care, requiring platforms to implement robust age verification and safety by design protocols by default.
- To navigate this complex legal matrix, technology developers must transition from reactive legal compliance to proactive ethical engineering. Adopting structured methodologies, such as the IEEE 7000 series standards and the ETHIC framework, is now essential for embedding human rights, transparency, and user agency directly into the software development lifecycle.
- To bridge the gap between theoretical ethics and practical software engineering, this study contributes a novel Fairness by Design lifecycle model. By synthesizing the ETHIC framework and the IEEE 7000 standard into the conventional Software Development Life Cycle, this proposed architecture offers organizations an operational blueprint to embed ethical risk assessments and algorithmic accountability directly into every phase of product development.

The era of evaluating digital success solely through the lens of hyper engagement and behavioral exploitation is rapidly concluding. As international regulatory bodies continuously refine and enforce stringent digital fairness mandates, corporate accountability will become inextricably linked to algorithmic transparency. Future market leadership in the digital economy will not belong to platforms that most effectively hijack human attention, but rather to those that successfully integrate ethical design and genuine value creation into their core technological architecture.

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Research Article

Ranking universities' graduate education performances through multi-criteria decision-making methods

Damla Yalçıner Çal*[a]

Department of Business Administration, Faculty of Economics and Administrative Sciences, Kafkas University, Kars, Türkiye

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Abstract

This study analyzes the performance of universities operating in Türkiye based on the number of graduate and specialty-level graduates by employing a multi-criteria decision-making (MCDM) approach. The dataset used in the research was obtained from the National Thesis Center's May 2026 database, and observations deemed unsuitable during the data preprocessing stage were excluded from the analysis. As a result, a final decision matrix consisting of 224 alternatives and 6 criteria (224×6) was constructed. Within the scope of the analysis, criterion weights were determined using the standard deviation method, an objective weighting technique that reflects the variability among criteria in the decision-making process. Subsequently, the MARCOS method was applied to calculate the performance scores of universities and establish their rankings. The findings revealed that Istanbul University, Gazi University, Marmara University, Hacettepe University, and Ankara University were the highest-performing universities. Their strong academic infrastructures, wide range of graduate programs, and high research capacities played a significant role in securing top positions in the ranking. In contrast, universities ranked at the lower end of the list were observed to possess more limited graduate education capacities. The results demonstrate that substantial differences exist among universities in Türkiye regarding graduate-level output. In conclusion, the integrated use of the standard deviation and MARCOS methods provided an objective and comparable framework for evaluating university performance. The study is expected to contribute to the development of higher education policies and support the strategic planning processes of universities.

1. Introduction

Today, higher education institutions play a significant role in the development processes of countries by contributing to knowledge production, the training of qualified human resources, and scientific advancement. The research capacity, academic productivity, and graduate education performance of universities are considered among the key factors determining the quality of higher education systems [1, 2]. For this reason, evaluating university performance through objective and comparable methods has become an important necessity for both policymakers and academic administrators. In particular, the number of graduate and specialty-level graduates is widely recognized as an important indicator reflecting the scientific production capacity and research-oriented structure of universities [3]. Decision-making processes are becoming increasingly complex due to the growing diversity of data and the need for multidimensional evaluations. In problems requiring the simultaneous consideration of multiple criteria, traditional decision-

*Corresponding author: damlayalciner@gmail.com
[a]orcid.org/0000-0002-9232-3063
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making approaches often remain insufficient, which has increased the importance of multi-criteria decision-making (MCDM) methods. MCDM methods provide decision-makers with an analytical and rational framework by enabling the systematic evaluation of alternatives under different criteria [4, 5]. These methods are widely used in many fields, including economics, engineering, healthcare, and education, and they produce effective results particularly in performance evaluation, ranking, and selection problems [6]. Recent studies conducted in the field of higher education also emphasize that MCDM methods provide reliable and effective outcomes in evaluating university performance [7].

One of the most critical stages in the MCDM process is the determination of criterion weights. Since criterion weights directly influence decision outcomes, it is essential that this process be carried out using objective methods as much as possible. In this context, the standard deviation (SD) method stands out as a statistically based objective weighting approach that assigns greater weights to criteria with higher variability by considering the distribution of criteria within the dataset [8]. The SD method is frequently preferred in the literature, especially in data-driven analyses, because it minimizes subjective evaluations. The use of objective weighting methods in university performance analyses contributes to a more accurate assessment of the differences among criteria [9]. Among the recently developed methods for ranking alternatives, the MARCOS (Measurement Alternatives and Ranking according to Compromise Solution) method has attracted considerable attention. The MARCOS method evaluates alternatives by comparing them with ideal and anti-ideal solutions, thereby enabling more consistent rankings [10]. The successful application of the method in different problem areas has contributed to its widespread adoption in the MCDM literature. In particular, it has been stated that the MARCOS method provides reliable results in performance evaluation and ranking problems and makes significant contributions to decision-making processes [11].

This study aims to evaluate the graduate and specialty-level performance of universities within the Turkish higher education system. For this purpose, graduate data obtained from the thesis database of the Council of Higher Education for January 2025 were used as the dataset. The criteria considered in the analysis consisted of six categories: Master's Degree, Doctorate, Medical Specialty, Proficiency in Arts, Dentistry Specialty, and Medical Subspecialty. Although the decision matrix initially included a broader dataset, several elimination procedures were carried out to ensure data integrity. Four universities with zero values across all criteria were excluded from the analysis. In addition, 35 universities that had a value in only one criterion while recording zero values in all remaining criteria were also excluded from the decision matrix. As a result of these procedures, the final decision matrix was constructed with dimensions of 224×6. Using the obtained dataset, criterion weights were objectively determined through the standard deviation method, and subsequently, university performance rankings were generated using the MARCOS method. In this respect, the study aims to contribute to the literature by evaluating the graduate and specialty-level output capacities of universities in Türkiye within a multi-criteria decision-making framework.

2. Literature Review

An examination of the multi-criteria decision-making (MCDM) literature reveals that standard deviation (SD)-based approaches occupy an important place among objective weighting methods used in the criterion weighting process. The SD method stands out as a statistical approach that assigns greater weights to criteria with higher variability by considering the distribution of data associated with each criterion. In this context, [8] compared the Entropy, CRITIC, and SD methods to examine how objective weighting approaches generate different results under varying data structures. Similarly, [12] proposed a new objective weighting method based on the impact of criterion removal and conducted comparative analyses with methods such as SD. [13] and [14] evaluated the effectiveness of several objective weighting methods, including SD, in determining criterion importance within the context of sustainable transportation problems. In addition, [15] analyzed the effects of objective and subjective weighting approaches on decision-making outcomes by considering both approaches together. More recent studies have further expanded the literature on SD-based methods. [16] introduced the ROCOSD method, which combines standard deviation and correlation-based weighting, thereby offering a new perspective to the literature. [17] examined the SD method within the framework of statistical weighting techniques, while [18] applied an improved criterion weighting approach based on standard deviation to MCDM problems. Collectively, these studies demonstrate that SD-based methods, both in their classical and enhanced forms, are widely employed in the literature. On the other hand, among the methods developed for ranking alternatives, the MARCOS method has emerged as one of the prominent approaches in recent MCDM studies. Developed by [19], this method is based on evaluating alternatives relative to ideal and anti-ideal solutions and was initially applied to sustainable supplier selection problems. Subsequent studies indicate that the method has been integrated with various approaches. For instance, [10] employed the integrated FUCOM-MARCOS model for evaluating human resources, while [20] addressed supplier selection problems using the Grey-MARCOS approach. Likewise, the D-MARCOS method proposed by [21] was applied to supplier selection in the iron and steel industry.

In the national literature, [22] jointly applied the MEREC and MARCOS methods to evaluate the social development levels of countries, whereas [23] analyzed the innovation performance of OECD and EU countries using the MEREC-MARCOS model. Furthermore, the type-2 neutrosophic MEREC-MARCOS model proposed by [24] extended the applicability of the method to decision-making problems involving uncertainty. In more recent studies, [25] utilized the MARCOS method in financial performance evaluation, while [26] incorporated the MARCOS method into a model involving machine learning and intuitionistic fuzzy MCDM approaches. Overall, the literature indicates that standard deviation-based weighting methods maintain a strong position due to their data-driven and objective structures, while the MARCOS method has been widely adopted across diverse application areas through integration with various MCDM techniques. This demonstrates that both approaches continue to preserve their relevance from both methodological and practical perspectives.

3. Methodology

3.1 Research Model

This section presents the methodology of the proposed model. In the proposed MCDM model, the criteria were weighted using the Standard Deviation method, and the weighted dataset was subsequently ranked through the MARCOS method. The methodological flowchart of the proposed model is presented in Figure 1.

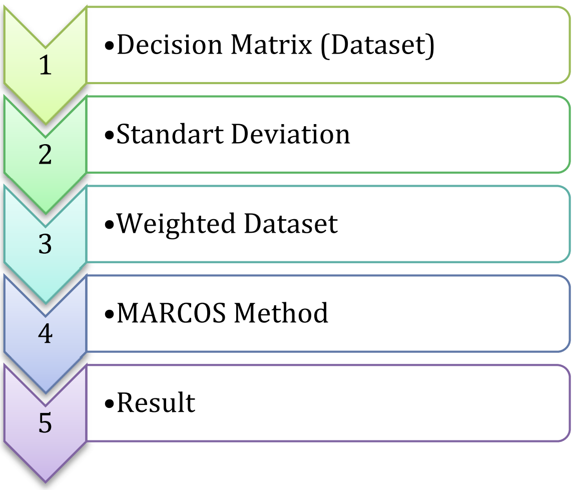

Figure 1. Flowchart of the Proposed Model

3.2. Dataset

The dataset used in this study includes the number of graduate and specialty-level graduates from universities operating in Türkiye and is based on the National Thesis Center's May 2026 data.

Within the scope of the analysis, six different criteria were taken into consideration. However, during the dataset preparation process, it was determined that the data structures of some universities were not suitable for the analysis. As a result of these elimination procedures, the final decision matrix constructed for the analysis consisted of 224 alternatives and 6 criteria (224×6). This structure ensured that the multi-criteria decision-making analysis was conducted on a balanced and suitable dataset. A portion of the dataset used in the application is presented in Table 1.

Table 1. Dataset

Code	University	Criterias					
		Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medical Subspecialty
A1	Abant İzzet Baysal University	1981	257	276	0	21	0
A2	Abdullah Gül University	175	65	0	0	0	0
A3	Acıbadem Mehmet Ali Aydınlar University	546	99	51	0	0	0
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
A221	Yüzüncü Yıl University	4002	706	714	0	12	9
A222	Zirve University	300	1	0	0	0	0
A223	Zonguldak Bülent Ecevit University	1536	212	315	0	126	0
A224	Zonguldak Karaelmas University	1040	103	245	0	0	0

Accordingly, Antalya Belek University, Gaziantep University of Science and Technology, National Intelligence Academy, Mudanya University, Semerkand Science and Civilization University, and Institute of Public Administration for Türkiye and the Middle East, which had zero values across all criteria, were excluded from the analysis. In addition, a total of 35 universities that had a value in only one criterion while recording zero values for all remaining criteria were also omitted from the decision matrix. These universities included Ministry of Justice, Adana Science and Technology University, Alanya Hamdullah Emin Paşa University, Alanya University, Ankara Science University, Antalya Bilim University, Beykoz University, Bursa Orhangazi University, Canik Başarı University, Naval Academy Command, Fenerbahçe University, Gaziantep Islamic Science and Technology University, Gedik University, Gediz University, Hakkari University, İpek University, Istanbul Atlas University, Istanbul Ayvansaray University, Istanbul Esenyurt University, Istanbul Kemerburgaz University, Istanbul Topkapı University, İzmir Tınaztepe University, Gendarmerie and Coast Guard Academy, Kahramanmaraş İstiklal University, Kapadokya University, Kocaeli Health and Technology University, Konya University, MEF University, Nuh Naci Yazgan University, OSTİM Technical University, Rize University, Süleyman Şah University, TED University, Yeni Yüzyıl University, and Yüksek İhtisas University.

3.3. Methods and Algorithms

3.3.1. Standard Deviation Method

The standard deviation method is a weighting approach based on the degree of variability exhibited by the values within a dataset [27]. In this method, criteria with similar values across alternatives are considered to have lower discriminating power; therefore, lower weights are assigned to such criteria. In this respect, the method follows a logic similar to the Entropy approach [14]. The implementation steps of the standard deviation method have been explained in detail in the literature and are summarized below [28, 29, 30]:

Step 1: The decision matrix is constructed using Equation (1).

$$IDM = \begin{bmatrix} x_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix} \tag{1}$$

Step 2: After constructing the decision matrix, the normalization process is performed. Benefit-oriented criteria are normalized using Equation (2), whereas cost-oriented criteria are normalized using Equation (3).

$$X_{ij}^{*} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{2}$$

$$X_{ij}^{*} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \tag{3}$$

i=1,2,…,m; j=1,2,…,n

Step 3: After calculating the standard deviation values of the criteria using Equation (4), the criterion weights are determined through Equation (5).

$$\sigma_j = \sqrt{\frac{\sum_{j=1}^{m}(x_{ij} - x_j)}{m}} j = 1 \qquad \text{j=1,…,n} \tag{4}$$

$$W_j = {\sigma_j}\Big/{\sum_{j=1}^{n}\sigma_j} \qquad \text{j=1,…,n} \tag{5}$$

3.3.2. MARCOS Method

The MARCOS method, introduced to the MCDM literature by Stević et al. in 2020, is one of the effective approaches used for the evaluation and ranking of alternatives. This method aims to determine performance rankings by considering the relationships between decision alternatives and ideal as well as anti-ideal reference points. The core principle of the method is based on analyzing the positions of alternatives relative to these two extreme reference points. Within the implementation process, utility functions are calculated for each alternative according to the defined relationships, and a compromise ranking is obtained through these functions. The preferences of the decision-maker are also reflected through these utility functions. The utility functions represent the position of an alternative relative to both the ideal and anti-ideal solutions. In this framework, the best alternative is identified as the option closest to the ideal solution and farthest from the anti-ideal solution [10, 22, 31, 32]:

Step 1: The decision matrix is constructed using Equation (1).

Step 2: The extended decision matrix is obtained by incorporating the ideal solution (AI) and anti-ideal solution (AAI) into the decision matrix and is calculated using Equation (6).

$$X = \begin{array}{c} C_n \\ A_1 \\ A_2 \\ \vdots \\ \vdots \\ A_m \\ AAI \\ AI \end{array} \begin{array}{c} C1, C2 \ldots. \\ \begin{bmatrix} x_{11} & x_{12} \cdots & x_{1n} \\ x_{21} & x_{22} \cdots & x_{2n} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} \cdots & x_{mn} \\ x_{aa1} & x_{aa2} \cdots & x_{aan} \\ x_{ai1} & x_{ai2} \cdots & x_{ain} \end{bmatrix} \end{array} \tag{6}$$

For benefit-oriented criteria, the calculation is performed using Equation (7), whereas for cost-oriented criteria, the calculation is carried out using Equation (8).

$$\begin{cases} AI = max_i x_{ij}, \text{benefit} - \text{oriented criteria } (j \in B) \\ AAI = min_i x_{ij}, \text{benefit} - \text{oriented criteria } (j \in B) \end{cases} \tag{7}$$

$$\begin{cases} AI = min_i x_{ij}, \text{cost} - \text{oriented criteria} (j \in C) \\ AAI = max_i x_{ij}, \text{cost} - \text{oriented criteria } (j \in C) \end{cases} \tag{8}$$

Step 3: The normalization of the extended decision matrix is calculated using Equation (9) for benefit-oriented criteria and Equation (10) for cost-oriented criteria.

$$n_{ij} = \frac{x_{ij}}{x_{ai}}, j \in B \tag{9}$$

$$n_{ij} = \frac{x_{aj}}{x_{ij}}, j \in C \tag{10}$$

The normalization of the generalized decision matrix is calculated using Equation (11).

$$N = \begin{bmatrix} n_{11} & n_{12} \dots & n_{1n} \\ n_{21} & n_{22} \cdots & n_{2n} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ n_{m1} & n_{m2} \cdots & n_{mn} \\ n_{aa1} & n_{aa2} \cdots & n_{aan} \\ n_{ai1} & n_{ai2} \cdots & n_{ain} \end{bmatrix} \tag{11}$$

Step 4: The weighted matrix is calculated using Equation (12) and Equation (13).

$$v_{ij} = n_{ij}.w_j \tag{12}$$

$$V = \begin{bmatrix} v_{11} & v_{12} \dots & v_{1n} \\ v_{21} & v_{22} \cdots & v_{2n} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} \cdots & v_{mn} \\ v_{aa1} & v_{aa2} \cdots & v_{aan} \\ v_{ai1} & v_{ai2} \cdots & v_{ain} \end{bmatrix} \tag{13}$$

Step 5: In order to measure the utility degrees of the decision alternatives, the sum of the weighted matrix elements is calculated using Equation (14), the utility degree relative to the ideal solution is determined using Equation (15), and the utility degree relative to the anti-ideal solution is calculated using Equation (16).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{14}$$

$$K_1^+ = \frac{S_i}{S_{ai}} \tag{15}$$

$$K_1^- = \frac{S_i}{S_{aai}} \tag{16}$$

Step 6: The utility function of the decision alternatives relative to the ideal solution is calculated using Equation (17), whereas the utility function relative to the anti-ideal solution is determined using Equation (18).

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{17}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{18}$$

Step 7: The utility functions of the alternatives are calculated using Equation (19).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i)}} \tag{19}$$

4. Findings

The study consists of two stages. In the first stage, the Standard Deviation method was employed to evaluate the performance criteria, while the MARCOS method was used to assess the universities. The criteria utilized in the study are presented in Table 2.

Tablo 2. Criterias

Sıra	Code	Description	Optimization
1	K1	Master's Degree	max
2	K2	Doctorate	max
3	K3	Medical Specialty	max
4	K4	Proficiency in Arts	max
5	K5	Dentistry Specialty	max
6	K6	Medicel Specialty	max

The alternatives used in the study are presented in Table 3.

Table 3. Alternatives

Code	University	Code	University
A1	Abant İzzet Baysal University	A113	Istanbul Health and Technology University
A2	Abdullah Gül University	A114	Istanbul Şehir University
A3	Acıbadem Mehmet Ali Aydınlar University	A115	Istanbul Technical University
A4	Acıbadem University	A116	Istanbul Commerce University
A5	Adana Alparslan Türkeş Science and Technology University	A117	Istanbul University
A6	Adıyaman University	A118	Istanbul University-Cerrahpaşa
A7	Adnan Menderes University	A119	Istanbul Yeni Yüzyıl University
A8	Afyon Kocatepe University	A120	Istanbul 29 Mayıs University
A9	Afyonkarahisar Health Sciences University	A121	İstinye University
A10	Ağrı İbrahim Çeçen University	A122	İzmir Bakırçay University
A11	Ahi Evran University	A123	İzmir Democracy University
A12	Akdeniz University	A124	İzmir University of Economics
A13	Aksaray University	A125	İzmir Katip Çelebi University
A14	Alanya Alaaddin Keykubat University	A126	İzmir University
A15	Altınbaş University	A127	İzmir Institute of Technology
A16	Amasya University	A128	Kadir Has University
A17	Anadolu University	A129	Kafkas University
A18	Ankara Hacı Bayram Veli University	A130	Kahramanmaraş Sütçü İmam University
A19	Ankara Medipol University	A131	Military Academy Command
A20	Ankara Music and Fine Arts University	A132	Karabük University
A21	Ankara Social Sciences University	A133	Karadeniz Technical University
A22	Ankara University	A134	Karamanoğlu Mehmetbey University
A23	Ankara Yıldırım Beyazıt University	A135	Kastamonu University
A24	Ardahan University	A136	Kayseri University
A25	Artvin Çoruh University	A137	Kyrgyzstan-Türkiye Manas University
A26	Atatürk University	A138	Kırıkkale University
A27	Atılım University	A139	Kırklareli University
A28	Avrasya University	A140	Kırşehir Ahi Evran University
A29	Aydın Adnan Menderes University	A141	Kilis 7 Aralık University
A30	Bahçeşehir University	A142	Kocaeli University
A31	Balıkesir University	A143	Koç University
A32	Bandırma Onyedi Eylül University	A144	Konya Food and Agriculture University
A33	Bartın University	A145	Konya Technical University
A34	Başkent University	A146	KTO Karatay University
A35	Batman University	A147	Kütahya Dumlupınar University
A36	Bayburt University	A148	Kütahya Health Sciences University
A37	Beykent University	A149	Lokman Hekim University
A38	Bezm-i Alem Vakıf University	A150	Malatya Turgut Özal University

A39	Bilecik Şeyh Edebali University	A151	Maltepe University
A40	Bingöl University	A152	Manisa Celal Bayar University
A41	Biruni University	A153	Mardin Artuklu University
A42	Bitlis Eren University	A154	Marmara University
A43	Boğaziçi University	A155	Mehmet Akif Ersoy University
A44	Bolu Abant İzzet Baysal University	A156	Melikşah University
A45	Bozok University	A157	Mersin University
A46	Burdur Mehmet Akif Ersoy University	A158	Mevlana University
A47	Bursa Technical University	A159	National Defense University
A48	Bursa Uludağ University	A160	Mimar Sinan Fine Arts University
A49	Bülent Ecevit University	A161	Muğla Sıtkı Koçman University
A50	Celal Bayar University	A162	Muğla University
A51	Cumhuriyet University	A163	Munzur University
A52	Çağ University	A164	Mustafa Kemal University
A53	Çanakkale Onsekiz Mart University	A165	Muş Alparslan University
A54	Çankaya University	A166	Namık Kemal University
A55	Çankırı Karatekin University	A167	Necmettin Erbakan University
A56	Çukurova University	A168	Nevşehir Hacı Bektaş Veli University
A57	Demiroğlu Science University	A169	Nevşehir University
A58	Dicle University	A170	Niğde Ömer Halisdemir University
A59	Doğuş University	A171	Niğde University
A60	Dokuz Eylül University	A172	Nişantaşı University
A61	Dumlupınar University	A173	Okan University
A62	Düzce University	A174	Ondokuz Mayıs University
A63	Ege University	A175	Ordu University
A64	Erciyes University	A176	Middle East Technical University
A65	Erzincan Binali Yıldırım University	A177	Osmaniye Korkut Ata University
A66	Erzincan University	A178	Özyeğin University
A67	Erzurum Technical University	A179	Pamukkale University
A68	Eskişehir Osmangazi University	A180	Piri Reis University
A69	Eskişehir Technical University	A181	Police Academy
A70	Fatih Sultan Mehmet Vakıf University	A182	Recep Tayyip Erdoğan University
A71	Fatih University	A183	Sabancı University
A72	Fırat University	A184	Ministry of Health
A73	Galatasaray University	A185	Health Sciences University
A74	Gulhane Military Medical Academy (GATA)	A186	Sakarya University of Applied Sciences
A75	Gazi University	A187	Sakarya University
A76	Gaziantep University	A188	Samsun University
A77	Gaziosmanpaşa University	A189	Sanko University
A78	Gebze Technical University	A190	Selçuk University
A79	Gebze Institute of Technology	A191	Siirt University
A80	Giresun University	A192	Sinop University
A81	Gümüşhane University	A193	Sivas Science and Technology University
A82	Hacettepe University	A194	Sivas Cumhuriyet University
A83	Haliç University	A195	Süleyman Demirel University
A84	War Academies Command	A196	Şırnak University
A85	Harran University	A197	Şifa University
A86	Hasan Kalyoncu University	A198	Tarsus University
A87	Hatay Mustafa Kemal University	A199	Tekirdağ Namık Kemal University
A88	Air Force Academy Command	A200	TOBB University of Economics and Technology
A89	Hitit University	A201	Tokat Gaziosmanpaşa University
A90	Khoja Akhmet Yassawi International Turkish-Kazakh University	A202	Toros University
A91	Iğdır University	A203	Trabzon University
A92	Isparta University of Applied Sciences	A204	Trakya University
A93	Işık University	A205	Tunceli University
A94	Ibn Haldun University	A206	Turgut Özal University
A95	İhsan Doğramacı Bilkent University	A207	Turkish Aeronautical Association University
A96	İnönü University	A208	Turkish-German University
A97	İskenderun Technical University	A209	Ufuk University
A98	Istanbul Arel University	A210	Uludağ University
A99	Istanbul Aydın University	A211	Uşak University
A100	Istanbul Beykent University	A212	Üsküdar University
A101	Istanbul Bilgi University	A213	Van Yüzüncü Yıl University
A102	Istanbul Bilim University	A214	Yalova University

A103	Istanbul Gedik University	A215	Yaşar University
A104	Istanbul Gelişim University	A216	Yeditepe University
A105	Istanbul Kent University	A217	Yıldırım Beyazıt University
A106	Istanbul Kültür University	A218	Yıldız Technical University
A107	Istanbul Medeniyet University	A219	Yozgat Bozok University
A108	Istanbul Medipol University	A220	Foreign Universities
A109	Istanbul Nişantaşı University	A221	Yüzüncü Yıl University
A110	Istanbul Okan University	A222	Zirve University
A111	Istanbul Rumeli University	A223	Zonguldak Bülent Ecevit University
A112	Istanbul Sabahattin Zaim University	A224	Zonguldak Karaelmas University

In MCDM methods, the first step is the construction of the decision matrix. In this context, the decision matrix, where the alternatives are represented in the rows and the criteria are represented in the columns, is presented in Table 4.

Table 4. Decision Matrix

Code	Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medicel Specialty
A1	1981	257	276	0	21	0
A2	175	65	0	0	0	0
A3	546	99	51	0	0	0
...	...	...	...	...	...	...
...	...	...	...	...	...	...
A221	4002	706	714	0	12	9
A222	300	1	0	0	0	0
A223	1536	212	315	0	126	0
A224	1040	103	245	0	0	0

4.1. Standard Deviation Analysis Results

As the first step in determining the importance levels of the criteria, all criteria were identified as benefit-oriented and normalized using Equation (2). The normalized decision matrix is presented in Table 5.

Table 5. Normalized Decision Matrix

Code	Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medicel Specialty
A1	0,0637	0,0196	0,0167	0,0000	0,0814	0,0000
A2	0,0056	0,0050	0,0000	0,0000	0,0000	0,0000
A3	0,0175	0,0075	0,0031	0,0000	0,0000	0,0000
...	...	...	...	...	...	...
...	...	...	...	...	...	...
A221	0,1287	0,0538	0,0432	0,0000	0,0465	0,0726
A222	0,0096	0,0001	0,0000	0,0000	0,0000	0,0000
A223	0,0494	0,0161	0,0191	0,0000	0,4884	0,0000
A224	0,0334	0,0078	0,0148	0,0000	0,0000	0,0000

After calculating the standard deviation of each column in the decision matrix using Equation (4), the weight of each criterion was determined through Equation (5), and the results are presented in Table 6.

Table 6. Criterion Weights

Criteria	Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medicel Specialty
Sd Wj	0,191646	0,172456	0,107591	0,131311	0,255378	0,141619

4.2. Results of the MARCOS Method

Within the scope of the MARCOS method, the decision matrix was first established using Equation (1). The relevant decision matrix was previously presented in Table 4. In the second step of the MARCOS method, the extended decision matrix was constructed using Equation (6) and Equation (7). The extended decision matrix is presented in Table 7.

Table 7. Extended Decision Matrix

Criteria	Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medicel Specialty
A1	1981	257	276	0	21	0
A2	175	65	0	0	0	0
A3	546	99	51	0	0	0
...	...	...	...	...	...	...
...	...	...	...	...	...	...
A221	4002	706	714	0	12	9
A222	300	1	0	0	0	0
A223	1536	212	315	0	126	0
A224	1040	103	245	0	0	0
MIN	2	0	0	0	0	0
MAX	31086	13127	16527	560	258	124

In the third step of the method, the values of the extended decision matrix were normalized using Equation (9) and Equation (11). The normalized values of the extended decision matrix are presented in Table 8.

Table 8. Normalized Extended Decision Matrix Values

Criteria	Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medicel Specialty
A1	0,0637	0,0196	0,0167	0,0000	0,0814	0,0000
A2	0,0056	0,0050	0,0000	0,0000	0,0000	0,0000
A3	0,0176	0,0075	0,0031	0,0000	0,0000	0,0000
...	...	...	...	...	...	...
...	...	...	...	...	...	...
A221	0,1287	0,0538	0,0432	0,0000	0,0465	0,0726
A222	0,0097	0,0001	0,0000	0,0000	0,0000	0,0000
A223	0,0494	0,0162	0,0191	0,0000	0,4884	0,0000
A224	0,0335	0,0078	0,0148	0,0000	0,0000	0,0000
MIN	0,0001	0,0000	0,0000	0,0000	0,0000	0,0000
MAX	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000

In the fourth step of the method, the weighted decision matrix values were calculated using Equation (12) and Equation (13). The weighted decision matrix is presented in Table 9.

Table 9. Weighted Decision Matrix

Criteria	Master's Degree	Doctorate	Medical Specialty	Proficiency in Arts	Dentistry Specialty	Medicel Specialty
A1	0,0122	0,0034	0,0018	0,0000	0,0208	0,0000
A2	0,0011	0,0009	0,0000	0,0000	0,0000	0,0000
A3	0,0034	0,0013	0,0003	0,0000	0,0000	0,0000
...	...	...	...	...	...	...
...	...	...	...	...	...	...
A221	0,0247	0,0093	0,0046	0,0000	0,0119	0,0103
A222	0,0018	0,0000	0,0000	0,0000	0,0000	0,0000
A223	0,0095	0,0028	0,0021	0,0000	0,1247	0,0000
A224	0,0064	0,0014	0,0016	0,0000	0,0000	0,0000
MIN	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
MAX	0,1916	0,1725	0,1076	0,1313	0,2554	0,1416

In the fifth step of the method, the utility degrees of the decision alternatives were calculated. First, the sum of the elements of the weighted matrix (S_i) was determined using Equation (14). Subsequently, the utility degrees relative to the ideal solution (K_i^+) were calculated using Equation (15), while the utility degrees relative to the anti-ideal solution (K_i^-) were determined using Equation (16). In this context, the utility degrees of the decision alternatives are presented in Table 10.

Table 10. Utility Degrees of Decision Alternatives

Code	S_i	K_i^+	K_i^-
A1	0,0122	0,0366	990,5000
A2	0,0011	0,0032	87,5000
A3	0,0034	0,0101	273,0000
...	...	...	...
...	...	...	...
A221	0,0350	0,1049	2834,6342
A222	0,0018	0,0055	150,0000
A223	0,0095	0,0284	768,0000
A224	0,0064	0,0192	520,0000

In the sixth step of the method, the utility function values of the decision alternatives relative to the ideal solution were measured using Equation (17), denoted as $f(K_i^+)$, while the utility function values relative to the anti-ideal solution were determined using Equation (18), denoted as $f(K_i^-)$. In the final step, the performance values of the universities—namely, the utility function values of the decision alternatives, $f(K_i)$—were calculated using Equation (19), and the rankings of these performance values were obtained. The calculated values are presented in Table 11.

Table 11. $f(K_i^+)$, $f(K_i^-)$, and $f(K_i)$ values

Code	$f(K_i^+)$	$f(K_i^-)$	$f(K_i)$
A1	0,99996	0,00004	0,03665
A2	0,99996	0,00004	0,00324
A3	0,99996	0,00004	0,01010
...	...	...	...
...	...	...	...
A221	0,99996	0,00004	0,10488
A222	0,99996	0,00004	0,00555
A223	0,99996	0,00004	0,02841
A224	0,99996	0,00004	0,01924

The ranking of the calculated values is presented in Table 12.

Table 12. $f(K_i)$ Ranking Values

Code	University	Rank	Code	University	Rank
A117	Istanbul University	1	A140	Kırşehir Ahi Evran University	113
A75	Gazi University	2	A128	Kadir Has University	114
A154	Marmara University	3	A52	Çağ University	115
A82	Hacettepe University	4	A200	TOBB University of Economics and Technology	116
A22	Ankara University	5	A87	Hatay Mustafa Kemal University	117
A60	Dokuz Eylül University	6	A70	Fatih Sultan Mehmet Vakıf University	118
A115	Istanbul Technical University	7	A65	Erzincan Binali Yıldırım University	119
A63	Ege University	8	A69	Eskişehir Technical University	120
A176	Middle East Technical University	9	A214	Yalova University	121
A184	Ministry of Health	10	A153	Mardin Artuklu University	122
A56	Çukurova University	11	A81	Gümüşhane University	123
A190	Selçuk University	12	A209	Ufuk University	124
A26	Atatürk University	13	A39	Bilecik Şeyh Edebali University	125
A12	Akdeniz University	14	A191	Siirt University	126
A218	Yıldız Technical University	15	A35	Batman University	127
A64	Erciyes University	16	A215	Yaşar University	128
A187	Sakarya University	17	A166	Namık Kemal University	129
A43	Boğaziçi University	18	A219	Yozgat Bozok University	130
A210	Uludağ University	19	A145	Konya Technical University	131
A195	Süleyman Demirel University	20	A162	Muğla University	132
A72	Fırat University	21	A47	Bursa Technical University	133
A142	Kocaeli University	22	A224	Zonguldak Karaelmas University	134

A174	Ondokuz Mayıs University	23	A107	Istanbul Medeniyet University	135
A68	Eskişehir Osmangazi University	24	A16	Amasya University	136
A76	Gaziantep University	25	A173	Okan University	137
A34	Başkent University	26	A124	İzmir University of Economics	138
A167	Necmettin Erbakan University	27	A146	KTO Karatay University	139
A30	Bahçeşehir University	28	A91	Iğdır University	140
A17	Anadolu University	29	A92	Isparta University of Applied Sciences	141
A133	Karadeniz Technical University	30	A139	Kırklareli University	142
A204	Trakya University	31	A10	Ağrı İbrahim Çeçen University	143
A220	Foreign Universities	32	A186	Sakarya University of Applied Sciences	144
A53	Çanakkale Onsekiz Mart University	33	A103	Istanbul Gedik University	145
A74	Gulhane Military Medical Academy (GATA)	34	A203	Trabzon University	146
A96	İnönü University	35	A177	Osmaniye Korkut Ata University	147
A157	Mersin University	36	A93	Işık University	148
A179	Pamukkale University	37	A137	Kyrgyzstan-Türkiye Manas University	149
A95	İhsan Doğramacı Bilkent University	38	A178	Özyeğin University	150
A130	Kahramanmaraş Sütçü İmam University	39	A6	Adıyaman University	151
A221	Yüzüncü Yıl University	40	A109	Istanbul Nişantaşı University	152
A99	Istanbul Aydın University	41	A119	Istanbul Yeni Yüzyıl University	153
A8	Afyon Kocatepe University	42	A207	Turkish Aeronautical Association University	154
A216	Yeditepe University	43	A36	Bayburt University	155
A132	Karabük University	44	A94	Ibn Haldun University	156
A58	Dicle University	45	A42	Bitlis Eren University	157
A48	Bursa Uludağ University	46	A32	Bandırma Onyedi Eylül University	158
A212	Üsküdar University	47	A192	Sinop University	159
A185	Health Sciences University	48	A141	Kilis 7 Aralık University	160
A138	Kırıkkale University	49	A165	Muş Alparslan University	161
A51	Cumhuriyet University	50	A159	National Defense University	162
A7	Adnan Menderes University	51	A49	Bülent Ecevit University	163
A85	Harran University	52	A97	İskenderun Technical University	164
A160	Mimar Sinan Fine Arts University	53	A21	Ankara Social Sciences University	165
A213	Van Yüzüncü Yıl University	54	A67	Erzurum Technical University	166
A125	İzmir Katip Çelebi University	55	A25	Artvin Çoruh University	167
A61	Dumlupınar University	56	A3	Acıbadem Mehmet Ali Aydınlar University	168
A50	Celal Bayar University	57	A181	Police Academy	169
A31	Balıkesir University	58	A172	Nişantaşı University	170
A37	Beykent University	59	A41	Biruni University	171
A161	Muğla Sıtkı Koçman University	60	A217	Yıldırım Beyazıt University	172
A55	Çankırı Karatekin University	61	A163	Munzur University	173
A83	Haliç University	62	A120	Istanbul 29 Mayıs University	174
A18	Ankara Hacı Bayram Veli University	63	A131	Military Academy Command	175
A194	Sivas Cumhuriyet University	64	A202	Toros University	176
A101	Istanbul Bilgi University	65	A100	Istanbul Beykent University	177
A23	Ankara Yıldırım Beyazıt University	66	A105	Istanbul Kent University	178
A29	Aydın Adnan Menderes University	67	A102	Istanbul Bilim University	179
A104	Istanbul Gelişim University	68	A123	İzmir Democracy University	180
A127	İzmir Institute of Technology	69	A14	Alanya Alaaddin Keykubat University	181
A151	Maltepe University	70	A121	İstinye University	182
A135	Kastamonu University	71	A38	Bezm-i Alem Vakıf University	183
A116	Istanbul Commerce University	72	A66	Erzincan University	184
A118	Istanbul University-Cerrahpaşa	73	A196	Şırnak University	185
A62	Düzce University	74	A155	Mehmet Akif Ersoy University	186
A112	Istanbul Sabahattin Zaim University	75	A11	Ahi Evran University	187
A201	Tokat Gaziosmanpaşa University	76	A24	Ardahan University	188
A129	Kafkas University	77	A5	Adana Alparslan Türkeş Science and Technology University	189
A152	Manisa Celal Bayar University	78	A28	Avrasya University	190
A183	Sabancı University	79	A45	Bozok University	191

A143	Koç University	80	A114	Istanbul Şehir University	192
A110	Istanbul Okan University	81	A206	Turgut Özal University	193
A98	Istanbul Arel University	82	A59	Doğuş University	194
A15	Altınbaş University	83	A111	Istanbul Rumeli University	195
A44	Bolu Abant İzzet Baysal University	84	A222	Zirve University	196
A170	Niğde Ömer Halisdemir University	85	A122	İzmir Bakırçay University	197
A78	Gebze Technical University	86	A198	Tarsus University	198
A79	Gebze Institute of Technology	87	A208	Turkish-German University	199
A108	Istanbul Medipol University	88	A84	War Academies Command	200
A175	Ordu University	89	A189	Sanko University	201
A71	Fatih University	90	A136	Kayseri University	202
A77	Gaziosmanpaşa University	91	A149	Lokman Hekim University	203
A147	Kütahya Dumlupınar University	92	A150	Malatya Turgut Özal University	204
A27	Atılım University	93	A2	Abdullah Gül University	205
A1	Abant İzzet Baysal University	94	A169	Nevşehir University	206
A199	Tekirdağ Namık Kemal University	95	A144	Konya Food and Agriculture University	207
A80	Giresun University	96	A188	Samsun University	208
A171	Niğde University	97	A20	Ankara Music and Fine Arts University	209
A13	Aksaray University	98	A148	Kütahya Health Sciences University	210
A46	Burdur Mehmet Akif Ersoy University	99	A88	Air Force Academy Command	211
A134	Karamanoğlu Mehmetbey University	100	A193	Sivas Science and Technology University	212
A168	Nevşehir Hacı Bektaş Veli University	101	A205	Tunceli University	213
A106	Istanbul Kültür University	102	A9	Afyonkarahisar Health Sciences University	214
A54	Çankaya University	103	A19	Ankara Medipol University	215
A86	Hasan Kalyoncu University	104	A158	Mevlana University	216
A182	Recep Tayyip Erdoğan University	105	A4	Acıbadem University	217
A73	Galatasaray University	106	A57	Demiroğlu Science University	218
A211	Uşak University	107	A156	Melikşah University	219
A223	Zonguldak Bülent Ecevit University	108	A180	Piri Reis University	220
A164	Mustafa Kemal University	109	A126	İzmir University	221
A89	Hitit University	110	A197	Şifa University	222
A40	Bingöl University	111	A113	Istanbul Health and Technology University	223
A33	Bartın University	112	A90	Khoja Akhmet Yassawi International Turkish-Kazakh University	224

When Table 12 is examined, the universities with the highest performance values based on graduation indicators are identified as Istanbul University, Gazi University, Marmara University, Hacettepe University, and Ankara University.

5. Conclusion

Higher education institutions play a critical role in the development processes of countries by contributing to knowledge production, the training of qualified human resources, and scientific advancement. For this reason, evaluating university performance through objective and comparable methods has become an important necessity for both policymakers and academic administrators. In particular, the number of graduate and specialty-level graduates is considered one of the key indicators reflecting the research capacity and academic productivity of universities. The literature also emphasizes that multi-criteria decision-making (MCDM) methods provide effective and reliable outcomes in performance evaluation processes [33, 34]. Accordingly, this study analyzed the performance of universities operating in Türkiye based on graduate and specialty-level graduate numbers within the framework of a multi-criteria decision-making approach. The dataset, constructed using the National Thesis Center’s May 2026 data, was transformed into a final decision matrix consisting of 224 alternatives and 6 criteria (224×6) after the necessary elimination procedures were completed. Previous studies have highlighted that university performance evaluations should incorporate multidimensional criteria and that MCDM methods offer effective solutions in this regard [7]. During the analysis process, criterion weights were objectively determined using the standard deviation method, and subsequently, university performance rankings were obtained through the MARCOS method. It has been stated in the literature that objective weighting methods produce more consistent and reliable results by considering the variability among criteria [9]. Furthermore, the widespread use of MCDM methods across various fields demonstrates that these approaches provide reliable support for decision-making processes [35]. From a methodological perspective, the integrated use of standard deviation-based weighting and the MARCOS method enabled the achievement of more objective and data-driven results by considering the variability among criteria. This demonstrates that the applied methodology provides distinctive and reliable outcomes in measuring university performance. In this respect, Stević et al. [19] stated that the MARCOS method provides strong outcomes in evaluating alternatives relative to ideal and anti-ideal solutions, while Zavadskas and Turskis [34] emphasized that MCDM methods are widely preferred in solving economic and managerial problems. According to the findings, the top five universities with the highest performance values were respectively Istanbul University, Gazi University, Marmara University, Hacettepe University, and Ankara University. The diversity of graduate programs, strong academic staff, and advanced research infrastructures of these universities are considered the primary factors supporting their top positions in the ranking. In addition, well-established universities such as Dokuz Eylül University, Istanbul Technical University, Ege University, and Middle East Technical University were also found to be concentrated among the upper ranks. This situation can be associated with the strong graduate program diversity, qualified academic staff, and advanced research infrastructures of these universities. Similarly, previous studies have emphasized that research-oriented universities tend to demonstrate higher performance in academic productivity indicators [36]. On the other hand, universities positioned at the lower levels of the ranking were generally observed to be newly established institutions or universities with limited graduate education capacity. This finding indicates that there are substantial differences among universities in Türkiye in terms of graduate-level output. Furthermore, it was observed that the majority of universities performing above the average performance value consisted of long-established and research-oriented institutions. A review of the literature indicates that studies ranking university performance through MCDM methods based specifically on graduate-level graduate data remain limited. Therefore, the present study contributes to the literature both in terms of the dataset employed and the methodology applied. Furthermore, the study demonstrates that university performance can be evaluated not only through publication and citation indicators but also through graduate education outputs. In conclusion, the findings reveal that universities in Türkiye exhibit significant differences in terms of graduate education and research capacity. Within this scope, it is recommended that universities with relatively low performance improve their graduate programs, strengthen their research infrastructures, and enhance academic incentive mechanisms. Future studies may compare ranking results using different MCDM methods and incorporate additional academic indicators such as publications, citations, project budgets, and international collaborations in order to provide a more comprehensive evaluation of university performance.

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Research Article

Fostering well-being in emerging adults through prosocial behavior: an intervention design proposal for higher education

Banu Çiçek Avcıoğlu[a*], Hüdayim Başak[b]

Department of Industrial Design Engineering, Gazi University, Ankara, Türkiye

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Abstract

This study presents a design and methodology paper that proposes a structured, theory-driven educational intervention to support prosocial behavior in emerging adulthood. Well-being is closely linked not only to individual satisfaction but also to social connectedness and resilience. Prosocial behaviors—deliberate acts of helping, sharing, and supporting others—emerge as fundamental determinants of both individual and collective well-being in this context. Emerging adulthood (ages 18–25) represents a critical developmental stage in which identity exploration and the formation of social roles take place, thereby offering an essential opportunity for educational interventions aimed at fostering prosociality. However, the literature reveals a scarcity of concrete applications specifically designed for this age group within the context of higher education. Addressing this gap, the present study aims to develop and propose a structured, theory-driven educational intervention that integrates design-based approaches with psychological frameworks to support prosocial behavior in emerging adulthood. This study proposes a 14-week course plan that integrates Participatory Design, Design Thinking, and Positive Psychology approaches to enhance university students' prosocial motivation. The COM-B model (capability, opportunity, motivation) and Self-Determination Theory (autonomy, competence, relatedness) constitute the theoretical foundation of the intervention. The unique contribution of this study lies in combining design education methodologies with behavior change theories to offer a scalable and practice-oriented intervention model tailored for higher education contexts. The research will be conducted using a quasi-experimental design with both experimental and control groups. Quantitative data will be collected through the VIA Character Strengths, Adult Prosociality, Basic Empathy, Psychological Need Satisfaction, PERMA well-being, and General Belongingness scales. In contrast, qualitative data will be obtained through interviews and focus group studies. The evaluation of the intervention's impact will be conducted in the subsequent main study, following the methodology proposed in this article.

1. Introduction

Well-being is defined as a multidimensional concept encompassing overall life satisfaction, the experience of positive emotions, and the perception of one's life as part of a meaningful whole. This phenomenon is not limited to individual psychological experiences but is also closely tied to the strength of social bonds and mutual trust within society [1–3]. The bonds individuals establish with themselves and their communities can even surpass basic physical needs as the strongest

*Corresponding author: bcavcioglu@gazi.edu.tr
[a]orcid.org/ 0000-0003-2517-0164; [b]orcid.org/ 0000-0001-8066-5384
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determinants of happiness and life satisfaction [4,5]. The most visible manifestation of such bonds emerges in prosocial behaviors. Historically, these behaviors have played a crucial role in ensuring survival and the continuation of generations, while also fostering a sense of belonging in society, serving as a cornerstone of social cohesion [6,7].

Prosocial behavior is defined as deliberate actions aimed at benefiting others. It includes not only cooperation but also voluntary acts such as donating, sharing, and helping those in need. [8–11]. Prosocial behaviors are considered indicators of sensitivity and care for others, as well as social well-being. Research highlights their positive associations with serotonin [12] and oxytocin [13] and points to their stress-regulating functions in cancer patients [14]. Furthermore, studies during the COVID-19 pandemic have emphasized the positive relationship between prosocial participation and individuals' sense of belonging, trust, and overall life satisfaction [15]. Within this framework, prosocial behaviors are viewed as significant behavioral outcomes for both individual and social health [16,17], serving as indicators of physical and psychological well-being [18]. While these concepts are closely interrelated, this study distinguishes prosocial behavior as a behavioral outcome, empathy as a cognitive–affective process, and social connectedness and well-being as broader psychosocial constructs.

Three initiating factors are necessary for an individual to engage in prosocial behavior: recognizing that another person needs help, perceiving this need accurately, and feeling self-efficacious in responding to it [19]. Earlier research focused primarily on "disadvantaged groups," whereas current studies have shifted toward the "motivational" dimension of prosociality. Thus, the central question has evolved from "How can disadvantaged groups be reached?" to "How can groups be motivated to help the disadvantaged?" In this sense, understanding another person's situation and engaging in action based on one's perceived competence constitutes a form of decision-making behavior [7], closely tied to social connectedness. Communities with higher social connectedness can more effectively facilitate access to support and resources. Lenzi et al. [20] argue that environmental social cohesion strengthens individuals' ties with their surroundings and encourages civic participation, suggesting that civic engagement can sometimes be viewed as a reflection of prosocial behavior. From this perspective, social cohesion is considered a crucial factor influencing community participation and promoting positive social behaviors [21].

This study conceptualizes its target group within the framework of emerging adulthood [22], which is recognized in psychological literature as a distinct developmental stage positioned between adolescence and adulthood, characterized by identity exploration, instability, and the development of social roles. Emerging adulthood (ages 18–25) is defined as the developmental phase following adolescence, during which individuals begin to assume adult roles such as career, marriage, and parenthood, often within the context of higher education [22]. During this period, young adults form new social networks and, for many, start living independently of their families. The autonomy gained through separation from family supports decision-making and perspective-taking, while the increasing importance of peer relationships contributes to the development of prosocial behavior [23–28].

Although this developmental stage entails risks such as a tendency toward risky behaviors, it is also seen as an opportunity to cultivate social responsibility through prosocial actions and positive guidance [29]. Prosocial behaviors in emerging adulthood are associated with a reduced likelihood of substance use [26] and improved physical and psychological health [16,30,31]. They also contribute positively to academic success [32], social competence, and the formation of healthy relationships [18,33]. Furthermore, groups with higher levels of prosociality demonstrate stronger identity formation, greater self-worth, fewer depressive symptoms, and higher overall prosocial engagement [34]. These findings suggest that prosocial behavior supports the development of positive and supportive relationships, thereby enhancing social well-being. Consequently, emerging adulthood represents a critical period for promoting engagement in prosocial activities [35].

Prosocial tendencies are observable from early developmental stages, and education plays a significant role in fostering prosocial development. Among university students, prosociality has been shown to increase alongside cognitive development [27,36]. Emerging adulthood, characterized by identity formation and social role exploration, represents a particularly critical period in which educational interventions can effectively shape prosocial tendencies. In this context, structured educational programs can support individuals in developing self-awareness, strengthening social connections, and enhancing overall well-being. However, despite the recognized importance of this developmental stage, existing research predominantly focuses on earlier periods such as infancy, childhood, and adolescence, leaving emerging adulthood relatively underexplored in terms of how prosocial behavior can be systematically supported [27,39–42].

Within the field of psychology, it has been noted that motivational approaches to prosociality often remain abstract and insufficiently translated into tangible experiences, limiting their practical applicability [43]. Sustaining prosocial behavior requires transforming these abstract principles into engaging and experience-based processes. In this context, product design education—emphasizing empathy, user-centered thinking, and solution-oriented development—offers a valuable framework for operationalizing prosocial behavior. Therefore, integrating prosociality-focused education with design interventions in higher education provides a promising pathway for embedding prosocial behavior into structured, experiential learning environments, thereby fostering resilience, empathy, and community participation among emerging adults.

Despite the growing body of research on prosocial behavior and well-being, existing studies predominantly focus on psychological or educational interventions in isolation, often lacking concrete, practice-oriented frameworks that translate prosociality into structured learning experiences within higher education. In particular, the integration of design-based approaches with prosocial behavior development remains underexplored. While design thinking emphasizes empathy and user-centered problem solving, its potential to systematically foster prosocial motivation and behavior has not been sufficiently articulated in the literature. Addressing this gap, the present study proposes a novel intervention model that combines participatory design, design thinking, and positive psychology within a course-based structure. This integrated approach aims to operationalize prosocial behavior as an experiential and design-driven learning process, thereby offering a scalable and practice-oriented contribution that extends beyond existing theoretical and educational models.

This study aims to enhance the prosocial motivation and well-being of emerging adults through education, focusing on the development of a semester-long, course-based intervention. The course first aims to cultivate awareness of the fundamental dynamics of prosocial behavior. Subsequently, participatory design practices will be employed to facilitate interaction with recipient groups, while positive psychology interventions will support self-efficacy. Design Thinking, which shares a similar starting point with prosociality and centers on empathy, will be applied throughout the process. This holistic approach aims to enhance students' prosocial motivation throughout a 14-week intervention.

In addition, the study contributes to societal well-being by fostering prosocial motivation among emerging adults in higher education. Through active engagement in the prosocial design process, participants are expected to experience enhanced autonomy, competence, and relatedness, as defined by Self-Determination Theory. Given the established relationship between these psychological needs and prosocial tendencies, the intervention is expected to strengthen prosocial motivation. Accordingly, the conceptual research foci are summarized as follows:

- Examining the effect of design thinking on empathy and prosocial motivation
- Evaluating the impact of learning support on perceptions of competence and prosocial participation
- Investigating the contribution of positive psychology and VIA character strengths to self-perception and prosocial behavior
- Exploring the relationship between participatory design, basic psychological need satisfaction (autonomy–competence–relatedness), and belonging
- Determining the level of change in the PERMA dimensions (positive emotion, engagement, relationships, meaning, accomplishment)

- Analyzing the impact of group interaction during the process on overall belonging

In the following sections, prior research is reviewed from an interdisciplinary perspective, with concrete examples of applications presented. The design and methodological framework of the course intervention are then explained, followed by a discussion of the expected findings and contributions.

2. Related Studies

A comprehensive review of the literature reveals that interventions based on prosocial behavior among undergraduate students have been examined in relation to mental health and well-being outcomes. Systematic searches were conducted across various databases, and only studies written in English that directly involved prosocial behavior interventions and targeted undergraduate populations were considered. After excluding publications that did not meet the inclusion criteria, a total of seven studies (Table 1) were identified, with most of them conducted in the United States, followed by a smaller number in Canada and the Netherlands. While the majority of these studies were published in the last decade, earlier examples from the 1990s were also included [44].

Nelson and colleagues [45] conducted their study with undergraduate students from both the United States and Korea, aged between 17 and 27. Participants were randomly assigned to perform kindness with autonomy support, kindness without support, or placed in a control group. The intervention highlighted that autonomy and competence play crucial roles in strengthening prosocial behavior and improving well-being, aligning strongly with Self-Determination Theory (SDT). While this study contributed valuable cross-cultural insights, its limitation was the short time frame, which did not allow for evaluating the long-term sustainability of prosocial behaviors across different cultural contexts.

Wang and colleagues [46] investigated a sample of 74 U.S. adults (average age 23.9, predominantly female). The intervention required participants to perform at least two generous acts each week, documented through diary reflections, compared with a control group. The study found that both groups reported improved life satisfaction and well-being, suggesting that intentional acts of generosity combined with self-reflection can enhance positive outcomes. However, the absence of a significant difference between experimental and control conditions raised questions about whether the improvements stemmed from the intervention or from time and contextual influences. The small sample size further limited generalizability.

Wienes and colleagues [47] studied 222 Dutch university students to examine how the target of prosocial acts influences outcomes. Students were randomized into groups practicing kindness toward strong ties (family/friends), weak ties (acquaintances/strangers), or treatment-as-usual. The results indicated that acts directed toward strong ties significantly improved well-being, while prosocial behavior toward weak ties increased stress levels. This highlighted the nuanced role of relational closeness in prosociality. Nonetheless, the study primarily measured short-term outcomes, leaving long-term contributions of prosociality toward weak ties underexplored, despite their potential for building broader social capital.

Little's research [48] focused on U.S. college students engaged in altruistic, unpaid volunteer activities. Rather than manipulating an intervention, the study examined the relationship between prosocial personality traits and well-being. Findings demonstrated clear links between prosocial orientation, constructive thinking, and enhanced self-perceptions. This contribution enriched the understanding of personality-based predictors of prosocial development. Still, the lack of detailed demographic data and unspecified sample size constrained the reliability and generalizability of the conclusions.

Whillans and colleagues [49] assessed the impact of volunteering and prosocial involvement on well-being across samples of university students and young adults. Their findings showed that prosocial participation contributed to increases in life satisfaction and subjective well-being, reinforcing the view that volunteering offers psychological benefits beyond altruistic outcomes. A limitation, however, was the contextual sensitivity of the findings: the positive effects of volunteering may depend on whether it is pursued voluntarily or perceived as obligatory, an aspect that was not deeply examined.

Stevick and Addleman [50] explored short-term volunteer experiences among U.S. college students. The research examined how temporary prosocial engagement influences self-perceptions and prosocial motivation. Results suggested that even brief volunteer activities positively shaped self-efficacy and prosocial orientation. The contribution of this study lies in showing that prosocial change can emerge even from limited interventions. However, the study did not track whether these changes endured over time, leaving the long-term stability of such effects uncertain.

Cheng [51] developed an experiential class project titled *FeedTheDeed*, implemented among psychology undergraduates. The intervention encouraged students to perform prosocial acts and share them via social media, turning kindness into both a behavioral and reflective learning process. This approach demonstrated how integrating digital platforms into higher education could boost engagement and concretize prosocial learning. The innovation was notable for linking prosocial education with modern communication tools. Yet, possible drawbacks—such as the risk of performative motivation through public posting—were not examined, limiting the study's exploration of unintended effects.

Taken together, the reviewed studies indicate that prosocial behavior interventions among undergraduate students generally lead to positive outcomes such as enhanced well-being, happiness, and empathy. These interventions are predominantly implemented through two main approaches: structured volunteering activities and small, self-initiated acts of kindness. While volunteering is associated with improved health and social connectedness, self-directed prosocial acts appear to be more effective in fostering autonomy and sustaining engagement over time. The recipients of such behaviors vary widely—from close social ties to strangers—highlighting the contextual diversity of prosocial experiences. However, despite these positive trends, the findings are not entirely consistent. In particular, externally imposed prosocial activities tend to reduce motivation and limit the overall impact of interventions. Moreover, a critical examination of the literature reveals several methodological limitations, including short intervention durations, small sample sizes, and a predominant reliance on quantitative measures. These limitations restrict a deeper understanding of participants' lived experiences and the long-term sustainability of prosocial behavior. Therefore, there is a clear need for more comprehensive, mixed-methods, and curriculum-integrated approaches that not only measure outcomes but also embed prosocial behavior within experiential and design-oriented learning processes in higher education contexts [44].

3. Theoretical Background

When examining the fundamental theories and dynamics influencing prosocial behavior, Susan Michie's COM-B model (Capability, Opportunity, Motivation, Behavior) stands out among widely accepted models in the behavior change literature, due to its guiding function, comprehensive scope, and applicability [52,54]. The model emphasizes that for a behavior to occur, the individual must first have a sense of capability regarding that behavior; in addition, the opportunity and motivation dimensions explain the conditions under which the behavior is enacted. Alongside this, the Self-Determination Theory (SDT), which provides a more detailed explanation of motivational processes, has also been prominent in the behavior change literature and in studies focusing on well-being [55,56].

3.1. Self-Determination Theory (SDT)

Self-Determination Theory (SDT) highlights three fundamental psychological needs: autonomy, relatedness, and competence (Fig. 1). The satisfaction of these needs is not only essential for well-being but also plays a decisive role in the emergence of prosocial behaviors [57]. Emerging adults tend to show higher levels of prosocial tendencies when they feel that their psychological needs are met. Research has shown that autonomy, in particular, is critical for prosocial behavior and is closely related to tendencies such as showing empathy and adopting different perspectives [58–64]. According to SDT, motivation exists on four levels, with intrinsic motivation being the most effective and applicable across many areas of life [29,65]. In this framework, meeting individuals' needs for autonomy, relatedness, and competence contributes to both the development of intrinsic motivation and the support of prosocial behaviors.

Table 1. Prosocial behavior interventions among undergraduate students [44]

Reference	Country of Publication	Sample size/Demographics	Intervention & Main Findings
Nelson et al. [45]	USA (data also from Korea)	USA: n=104, age 17–24 (M=19.1), 61% women; Korea: n=114, age 18–27 (M=20.7), 46% women	Randomized to kindness with/without support, or control. Autonomy and competence are linked to improved well-being.
Wang et al. [46]	USA	n=74, age ≥18 (M=23.9), 84% women	Experimental intervention vs control. At least two generous acts per week, diary reflections. Both groups improved life satisfaction & well-being.
Wieners et al.[47]	Netherlands	n=222, M age=21.3, 74% women	Randomized to kindness toward strong ties, weak ties, or treatment-as-usual. Strong ties condition improved well-being, weak ties increased stress.
Little [48]	USA	not specified (college volunteers)	Examined altruistic, unpaid volunteer positions. Found links between prosocial personality traits and well-being.
Whillans et al. [49]	USA	Sample details not specified	Volunteering did not directly improve well-being. Highlighted the importance of motivation and participation context.
Stevick & Addleman [50]	USA	Sample details not specified	Short-term volunteer experiences improved self-efficacy and prosocial behavior, but long-term impacts were unclear.
Cheng [51]	Canada	Sample details not specified	"Feed the Deed" project: small acts of kindness increased happiness and positive emotions.

3.2. COM-B Model for Behavior Change

The COM-B model proposes that behavior emerges as the result of the interaction among three fundamental components: capability, opportunity, and motivation. Capability refers to an individual's capacity to perform a behavior and is divided into two types: physical (bodily skills and health) and psychological (knowledge and cognitive skills). Opportunity encompasses the environmental and social factors that facilitate or hinder the behavior; these are classified as physical opportunities (time, space, resources) and social opportunities (norms, social support). Motivation determines the individual's willingness to perform the behavior and is considered in two dimensions: reflective motivation (conscious intentions, goals) and automatic motivation (habits, emotions, impulses). The interaction of these three elements shapes the behavior itself [67].

At the second level of the COM-B model, intervention functions used to support behavior change are defined, including education, persuasion, incentivization, coercion, training, environmental restructuring, modeling, and enablement. At the third level, policy categories that facilitate the implementation of these interventions are outlined, such as communication and marketing, guidelines, fiscal measures, regulation, legislation, environmental and social planning, and service provision (Fig. 2). Within the course design developed in this study, the intervention functions emphasized are particularly education, training, modeling, and enablement.

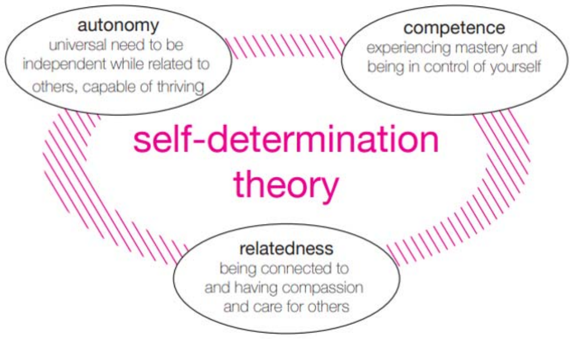

Fig. 1. Self-Determination Theory [66]

4. Methodology

This study, focusing on emerging adults in higher education, aims to strengthen design students' prosocial behavior motivation through a course-based intervention. The design challenge addressed within the course involves supporting first-year students in their integration into university life by developing prosocial solutions created by third-year students. In this way, the adjustment of first-year students is facilitated, while simultaneously enhancing the prosocial motivation of third-year students. Unlike many previous studies characterized by short-term interventions, the present study adopts a 14-week course-based structure to allow sufficient time for experiential learning, iterative design processes, and the gradual internalization of prosocial behaviors. This extended duration enables students to move beyond surface-level engagement toward sustained behavioral change. Furthermore, the participant group is embedded within an authentic higher education context, ensuring ecological validity while allowing the integration of prosocial behavior development into an existing curriculum. In this way, the study directly addresses key methodological limitations in the literature by combining extended duration with a contextually grounded and practice-oriented design.

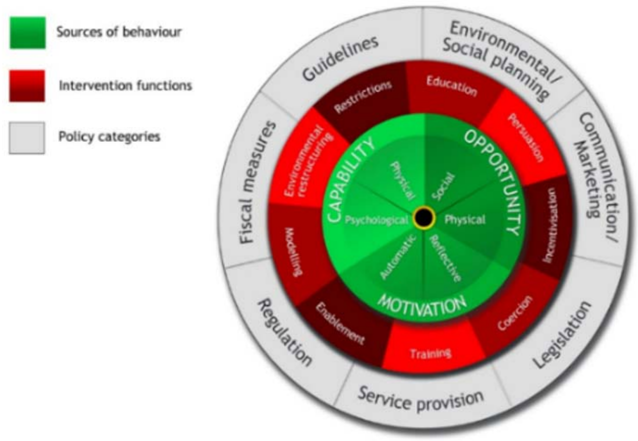

Fig. 2. Components of the COM-B Model for Behavior Change [67]

This intervention plan (Fig. 3) systematically illustrates the multilayered relationship between the theoretical framework and the expected outcomes. At the theoretical level, Self-Determination Theory (SDT) and the COM-B model serve as key foundations for explaining students' motivational processes and behavior change. At the course intervention level, the integration of prosocial behavior training, positive psychology, participatory design, and design thinking approaches enables the translation of these theories into tangible practices within the learning environment. These components are designed to enrich students' experiences of developing prosocial behavior through empathy, fostering belonging, engaging in creative problem-solving, and practicing collaborative learning. At the outcome level, the intervention is expected to strengthen students' prosocial motivation while simultaneously enhancing their overall well-being. As illustrated in the framework, a holistic methodological chain is constructed—linking theoretical foundations to practical interventions and, ultimately, to behavioral and psychosocial outcomes.

4.1. Prosocial Behavior Education

Within the course, a dedicated instructional session on prosocial behavior aims to provide students with knowledge and awareness of prosocial behavior dynamics. At the end of the session, an online quiz conducted through the Mentimeter platform will be used to reinforce knowledge retention. This activity is designed to strengthen the capability component required for prosocial action. In addition, examples of prosocial behaviors that can be applied both among course participants and later in participatory design workshops will be discussed, allowing students to concretize the concept, practice behaviors, and reinforce them. In this way, physical and social opportunities are created to support prosocial action. These activities are expected to enhance students' perceived competence and foster a sense of belonging through group interaction.

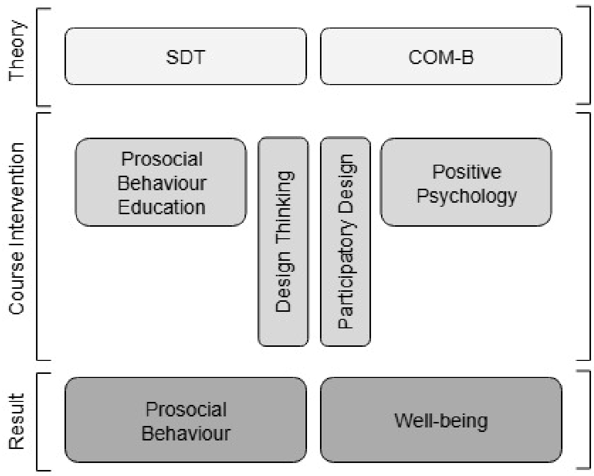

Fig. 3. Course Intervention Plan

4.2. Participatory Design

Although often regarded as a design method, Participatory Design is essentially a research approach. Its primary aim is not only to understand an existing practice but also to collaboratively envision, shape, and transcend it in ways that participants find meaningful [68]. Participants are not merely supporting actors but active contributors who enrich the diversity of knowledge and form an integral part of the design process. This allows tacit or embedded forms of knowledge to surface, bridging the analytical expertise of the designer with the experiential insights of participants.In the course, Participatory Design serves as a critical foundation for experiential learning of prosocial dynamics. First-year students will be involved as the participant group, sharing their needs and challenges based on their adjustment experiences to university life. Third-year students will act as the designer group, creating solutions that address these needs and support first-year students' integration into university life. Through this process, the fundamental prosocial steps of "observing a need, making sense of it, and responding to it" are turned into a concrete experience. Since full participation by all first-year students is not feasible, a representative group will be selected to voice their experiences. This structure ensures that tacit user knowledge (from first-years) is revealed and transformed by the designer group (third-years) into prosocial solutions. Thus, Participatory Design not only leads to more effective interventions but also strengthens students' self-efficacy, empathy, and sense of belonging.

4.3. Character Strengths Exploration Through VIA Inventory

According to Self-Determination Theory (SDT), intrinsic motivation and self-perception are critical factors for prosocial behavior [7,43,69]. Developing self-awareness is shown to positively impact psychological health and well-being [69]. Literature highlights the role of character strengths in enhancing individual well-being, social participation [40], and the link between prosocial behavior and self-efficacy [71]. Related constructs such as Self-Concept Clarity (SCC), self-efficacy, and character strengths complement SDT by providing a broader lens to understand prosocial behavior in relation to identity development and well-being. Individuals with higher SCC—those who have a clear and consistent self-definition—are more likely to engage in prosocial acts, display self-confidence, and build stronger social relationships [72,73].

The VIA Character Strengths framework, developed by Seligman et al. [74], which measures 24 character strengths, is one of the most widely applied tools for identifying strengths. These strengths are universal across cultures, contribute to satisfaction and happiness, and represent moral values. They are measurable, distinct, and observable in varying degrees among individuals, including children and adolescents. Research shows that using character strengths fosters positive self-worth, enhances achievement capacity, and supports potential realization [75,76]. Thus, integrating VIA into the intervention allows students to recognize their unique strengths, reinforce self-efficacy, and cultivate prosocial orientations.

4.4. Design Thinking

For an individual to act prosocially, they must first understand the needs of others and empathize with them [7]. The design process similarly begins with empathy, enabling designers to create solutions that positively impact users' lives. In this respect, Design Thinking is considered one of the most suitable methods for addressing social innovation [77]. Design Thinking extends beyond traditional product design to tackle complex societal challenges. Its purpose is not merely to produce objects but to reimagine human experiences, interactions, and services. At its core lies empathy—since users may not always articulate their needs, designers must observe, interpret, and develop meaningful solutions. The approach encompasses five iterative stages: empathize, define, ideate, prototype, and test (Fig. 4). These stages form a cyclical process, continually refined through user insights. In the context of higher education, integrating Design Thinking offers students opportunities to build empathy, collaborate in problem-solving, and generate tangible outputs. By engaging in this human-centered process, students not only learn design as a skill but also internalize prosocial behavior through collaborative creation. This highlights the potential of Design Thinking as a driver for both educational outcomes and social well-being [78].

4.5. Methodology from the Perspective of COM-B and SDT

The prosocial behavior education embedded in the course is primarily intended to strengthen the capability component of the COM-B model. By increasing students' knowledge, awareness, and skills regarding prosocial behavior dynamics, their psychological and behavioral capacities are expected to improve. In this study, capability is primarily addressed in its psychological dimension (e.g., empathy, awareness, and perspective-taking), while physical capability—understood as bodily or motor capacity—is not directly targeted within the scope of the intervention. Instead, the physical learning environment, including the design studio and collaborative settings, is considered as part of the opportunity component. Classroom activities are designed to contribute to the opportunity dimension by providing contexts for practicing and reinforcing prosocial behaviors, while group interactions are anticipated to enhance motivation by fostering a stronger sense of belonging. This approach is likely to support the psychological needs of autonomy, competence, and relatedness identified by Self-Determination Theory (SDT). In this sense, the intervention aims to holistically address both the key elements of behavior change emphasized in COM-B and the psychological needs deemed critical for motivation and well-being in SDT.

The participatory design process is also expected to align closely with this theoretical framework. From a COM-B perspective, the needs expressed by first-year students render the opportunity dimension visible, while the design responses of third-year students are anticipated to strengthen capability and motivation. From an SDT perspective, the process is expected to enhance students' experiences of autonomy, competence, and relatedness—thereby supporting not only the quality of design outcomes but also prosocial motivation and well-being. In this way, participatory design functions not merely as a method but as a learning experience that operationalizes the dynamics of behavior change and motivation outlined in COM-B and SDT. The inclusion of positive psychology through character strengths education is assumed to complement this framework further. By recognizing and utilizing their personal strengths, students are expected to increase their self-awareness, reinforce their sense of competence, and activate their potential more effectively. This process may also contribute to the fulfillment of autonomy, competence, and relatedness needs, thereby fostering prosocial motivation.

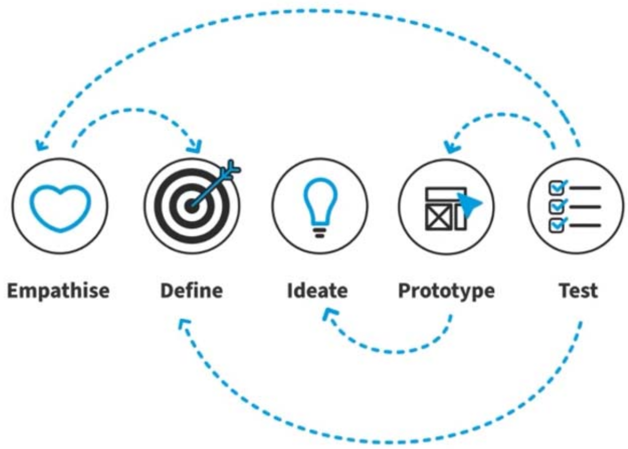

Fig. 4. Stages of Design Thinking [79]

Finally, the Design Thinking process is anticipated to intersect directly with both models. Within COM-B, the required elements for behavior—capability, opportunity, and motivation—find tangible expression across the stages of Design Thinking: empathy, problem definition, ideation, prototyping, and testing. The empathy and problem definition stages are expected to help students better understand user needs; the participatory design element creates social opportunities; and the prototyping and testing stages make behavioral outcomes visible, thereby enhancing motivation. From an SDT perspective, the process contributes to autonomy (active engagement in ideation), competence (hands-on problem-solving and prototyping), and relatedness (empathy and user interaction), thus nurturing the intrinsic motivation essential for prosocial behavior. The relationship between the approaches and methods integrated into the course design and the underlying behavior change theories is summarized in Table 2.

4.6. Data Collection and Analysis Plan

4.6.1 Quantitative Data Collection Tools

The course intervention will include two rounds of scale administration, one at the beginning and one at the end of the semester. This will enable a time-based comparison to assess the intervention's contributions by examining the differences between pre-test and post-test results. Five scales will be administered simultaneously to both the experimental group (students enrolled in the course) and the control group (students not enrolled in the course): the Adult Prosociality Scale, the Basic Empathy Scale, the Need Satisfaction Scale, the General Belongingness Scale, and the PERMA Profiler. In addition, the VIA Character Strengths Inventory will be administered once, exclusively to the experimental group, to raise awareness of individual strengths.

Participant Information Form: At the very beginning of scale administration, this form will ensure anonymity by assigning IDs to participants, while also collecting demographic and personal information (e.g., age, gender, year of study, living situation, economic conditions, social support). It will also include questions about psychological history, prior volunteering experiences, and stress levels, allowing for an analysis of the relationship between prosocial motivation and individual differences.

VIA Character Strengths Inventory: Developed by Peterson and Seligman [80], this instrument measures 24 character strengths and is widely validated across cultures. In this study, the VIA Institute on Character's Researcher Dashboard will be used for its online administration and automatic reporting features. The test is expected to enhance students' positive self-perceptions during the intervention.

Table 2. Course intervention component– related model – contribution

Component/ Method	Targeted Component	Contribution
Prosocial Behavior Education	COM-B – Capability	Enhancing knowledge, awareness, and skills related to prosocial behavior dynamics
In-Class Activities	COM-B – Opportunity	Creating social environments and experiential opportunities for practicing and reinforcing behaviors
Group Sharing	COM-B – Motivation / SDT – Relatedness	Strengthening a sense of belonging, thereby increasing social motivation and connectedness
Participatory Design	COM-B – Capability, Opportunity, Motivation	Enabling students to identify needs and generate solutions; making opportunities more visible
	SDT – Autonomy, Competence, Relatedness	Supporting active participation, problem-solving experience, and strengthening social bonds through empathy
Positive Psychology/ Character Strengths	SDT – Competence, Autonomy, Relatedness	Increasing self-efficacy through recognition and use of strengths; supporting autonomy and belonging.
Design Thinking Process	COM-B – Capability, Opportunity, Motivation	Facilitating understanding of needs through empathy and problem definition; increasing motivation through prototyping and testing
	SDT – Autonomy, Competence, Relatedness	Supporting autonomy through idea generation, competence through prototyping, and relatedness through empathy

The course process was designed as a gradual and holistic structure that enables prosocial behavior to be experienced within the design process rather than merely learned conceptually. In the initial weeks, the aim was for students to understand the theoretical foundations of prosocial behavior, participatory design, and Design Thinking approaches. Self-awareness and motivational aspects were further supported through the VIA Character Strengths Inventory and example applications. This stage was structured as a cognitive preparation phase that provides a foundation for the "psychological capability" component of the COM-B model and the "autonomy" dimension of Self-Determination Theory (SDT).

In the following weeks, user experiences were made visible through empathy maps and needs analyses, enabling students to better understand the university adaptation processes of first-year students. This phase constituted a critical threshold for recognizing social opportunities and supporting the need for relatedness. During the second half of the process, ideation, prototyping, and testing activities were conducted. Students iteratively refined their solutions based on peer feedback and user interactions. These practice-based stages strengthened students' sense of competence while creating an iterative learning cycle that supports the transformation of motivation into behavior. Finally, the presentations and evaluation sessions conducted at the end of the semester reinforced the reflective dimension of the process and contributed to the internalization of the design activity as a prosocial learning experience.

Adult Prosociality Scale: Developed by Caprara et al. [81], this tool assesses prosocial tendencies, including helping, sharing, cooperation, and altruism. It will provide direct evaluation of the changes in prosocial motivation resulting from the intervention.

Basic Empathy Scale: Developed by Jolliffe and Farrington [82], this scale measures both cognitive and affective empathy, allowing for an examination of how empathy—an essential component of prosocial behavior—is influenced by the course intervention.

Need Satisfaction Scale: Developed by Deci and Ryan [83] within the framework of Self-Determination Theory, this instrument evaluates the satisfaction of basic psychological needs: autonomy, competence, and relatedness. It will assess how the intervention contributes to SDT's motivational processes.

General Belongingness Scale: Developed by Malone, Pillow, and Osman [84], this scale measures individuals' sense of social belonging. It will help determine whether students' group bonds and social connectedness are strengthened during the intervention.

PERMA Scale: Developed by Butler and Kern [85], based on Seligman's PERMA model, this scale evaluates five domains: positive emotion, engagement, relationships, meaning, and accomplishment. It will measure the effects of the intervention on students' overall well-being.

4.6.2 Qualitative Data Collection Tools

Semi-Structured Interview Form: This tool will be used to explore in depth the experiences of students in the experimental group, including their perceptions of the participatory design and design thinking processes, group interactions, and relational needs. It will also help assess the perceived impact of the course on prosocial motivation, empathy, autonomy, a sense of belonging, and positive emotions.

Observation Form: This tool will allow for direct observation of students' behaviors, group interactions, and prosocial tendencies during the course. It will provide real-time feedback on class dynamics, contributing to the identification of strengths and areas for improvement in the intervention.

4.6.3 Data Analysis

Quantitative data will be analyzed in SPSS using dependent and independent t-tests to compare scale scores between the experimental and control groups. This will allow not only for an assessment of changes in prosocial motivation but also for an examination of how these changes are reflected in related domains such as empathy, belonging, need satisfaction, and well-being. Qualitative data will be analyzed through descriptive content analysis using NVivo, providing contextual insights from students' experiences to complement quantitative results and offer a more holistic evaluation.

5. Expected Findings and Contributions

The proposed intervention is anticipated to contribute to enhancing prosocial motivation among emerging adults in higher education. Prosocial motivation, defined as the willingness to act in ways that benefit others, is considered an important factor in shaping social responsibility, collaboration, and community-oriented behaviors during early adulthood. By integrating structured educational activities that emphasize empathy, reflection, and collaborative engagement, the intervention is designed to provide opportunities for students to develop a deeper awareness of their impact on others and their surrounding communities. Beyond prosocial motivation, the intervention is likely to influence several psychological and social dimensions. Increases in empathy, perceived belonging, and social connectedness may emerge as students participate in collaborative and participatory learning environments. Activities centered on character strengths identification are intended to support students in recognizing their personal capacities and applying them in socially meaningful contexts. This process may contribute to strengthening self-efficacy and encouraging students to perceive themselves as active contributors to social well-being. Furthermore, the participatory design process and group-based projects incorporated in the intervention are expected to facilitate a stronger sense of belonging and collective responsibility. Through collaborative ideation, prototyping, and project development, students may experience increased engagement with their peers and develop a deeper appreciation for cooperative problem-solving. These experiences are likely to support both individual psychological development and the cultivation of a more supportive and prosocial learning environment. From a methodological perspective, the mixed-methods design of the study is intended to provide a comprehensive understanding of the intervention's potential effects. Quantitative findings are expected to offer measurable indications of changes in prosocial motivation and related constructs, while qualitative insights are anticipated to enrich the understanding of students' experiences, perceptions, and reflections throughout the intervention process. Finally, this study seeks to contribute to the literature by presenting a structured educational model that demonstrates how prosocial motivation may be fostered in higher education contexts. By integrating design thinking, participatory design, and positive psychology, the study offers an interdisciplinary framework that bridges design education and psychological well-being research, thereby addressing a notable gap in the existing literature.

6. Limitations

The study focuses on emerging adults aged 18–25, representing the transitional stage between adolescence and adulthood. The design and implementation of products and services will be limited to applications within the campus context. Consequently, the study sample will be restricted to Industrial Design Engineering students at Gazi University, ensuring accessibility for observation and data collection in both experimental and control groups.

7. Ethical Statement

As this article presents a course intervention proposal rather than the implementation itself, formal approval from the university's Ethics Committee was not required at this stage.

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Research Article

Individual innovativeness and attitudes toward artificial intelligence among student pilots

Seda Çeken[*1a], Arif Tuncal[*2b]

[1] *Department of Aviation Psychology, İstanbul University Institute for Aviation Psychology Research, İstanbul University, İstanbul, Türkiye*
[2] *Department of Aviation Systems and Technologies, International Science and Technology University, Warsaw, Poland*

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Abstract

This study examines the relationships among individual innovativeness, use of AI-based tools, and attitudes toward AI among student pilots. Drawing on technology acceptance and human–AI interaction perspectives, the study aims to identify how both dispositional and experiential factors shape AI attitudes in a high-technology domain. Data were collected from 204 student pilots in Türkiye using a convenience sampling method. The study employed validated scales to measure individual innovativeness and attitudes toward AI. The collected data were analyzed using descriptive statistics, correlation analysis, reliability tests, and path analysis. The results indicate that individual innovativeness has a positive and significant effect on attitudes toward AI, while the use of AI-based tools emerges as a stronger predictor. Additionally, a small but significant relationship was found between innovativeness and AI usage. These findings suggest that attitudes toward AI are shaped by both personal tendencies and direct interaction with AI technologies. The study contributes to the literature by integrating human–AI interaction and technology acceptance perspectives in the aviation context and highlights the importance of experiential learning and psychological readiness for effective AI integration.

1. Introduction

The aviation industry is a prime example of a sociotechnical domain in which humans and technology operate in close coordination through highly automated operational systems [1, 2]. Advances in flight management systems, decision-support tools, and intelligent automation technologies have not only reshaped human–technology interaction in terms of operational efficiency, but also through cognitive and behavioural adaptation processes. This suggests that the role of humans in automation has evolved from passive users to integral components of joint cognitive systems [3]. With the growing implementation of artificial intelligence (AI)-based systems in aviation in recent years, traditional human–automation interaction has increasingly shifted toward a human–AI teaming perspective [4]. Human–AI teaming involves collaborative arrangements in which humans and AI systems work together through information sharing, shared situation awareness, joint decision-making, and coordinated task execution [5]. This perspective is particularly relevant in high-reliability aviation operations, where the integration of human expertise and intelligent systems is increasingly recognized as a new operational paradigm that supports safety, resilience, and performance [6].

*Corresponding author: sedaceken@istanbul.edu.tr
[a]orcid.org/0000-0002-5870-2246, [b]orcid.org/0000-0003-4343-6261
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Human–AI teaming is increasingly viewed in high-reliability domains, such as aviation, not merely as a technological advancement, but as a transformation that requires examination through a human factors lens. In this regard, the Artificial Intelligence Roadmap 2.0 published by the European Union Aviation Safety Agency (EASA), together with emerging regulatory AI frameworks, indicates that AI is expected to be progressively integrated into pilot operations through applications ranging from cockpit support systems and intelligent decision aids to virtual co-pilot solutions and advanced task-sharing architectures [7]. These developments reinforce the notion that AI is not intended to replace pilots, but rather to increasingly function as a "teammate" within future flight operations.

Recent literature further supports this transformation. AI-enabled virtual co-pilot systems, explainable decision-support mechanisms, intelligent cockpit interfaces, and discussions surrounding extended minimum crew operations suggest that future pilots will be evaluated not only in terms of manual and cognitive competencies but also in terms of their ability to collaborate effectively with intelligent systems [8, 9, 10]. Particularly in debates surrounding single-pilot operations and advanced automation, human–AI collaboration is increasingly considered a critical component for maintaining safety and operational resilience [11, 12]. In this context, the pilot's role is evolving from that of a traditional "aircraft operator" toward that of a "human–AI team member" capable of coordinating with AI-supported systems [8, 9].

This transformation also raises important questions regarding pilot education and the individual characteristics that may shape the profile of future aviators. In this respect, student pilots represent a particularly critical population. As future operators expected to work in increasingly digitalized and AI-intensive flight environments, they constitute key stakeholders in this transition. Moreover, the global pilot shortage, ongoing digital transformation in aviation training, and the growing use of intelligent training technologies suggest that student pilots should be evaluated not only in terms of technical competence but also in terms of their adaptability to emerging technologies and openness to innovation [13, 14].

Despite the growing body of literature on AI in aviation, existing research has predominantly focused on technological capabilities, acceptance of automation, trust in intelligent systems, and the operational implications of human–AI collaboration. Relatively little attention has been given to the personal traits that could influence future pilots' attitudes toward AI, particularly among student pilots. In this regard, individual innovativeness may be a critical yet under-explored factor, as it reflects an individual's openness to new ideas, their willingness to adopt emerging technologies, and their tendency to embrace change. All of these factors may be particularly relevant in AI-enabled aviation environments. At the same time, attitudes toward AI are likely to play a significant role in shaping how future pilots perceive, accept, and collaborate with intelligent systems. Against this backdrop, investigating the relationship between student pilots' individual innovativeness and their attitudes toward AI may contribute to a deeper understanding of human readiness for future AI-supported flight operations. Accordingly, the present study aims to investigate this relationship. Addressing this relationship will contribute to the emerging literature on human–AI teaming from an aviation psychology perspective and offer practical implications for pilot selection, training, and developing future-oriented competencies in increasingly intelligent aviation systems.

2. Literature Review and Hypothesis Development

2.1. Individual Innovativeness

Individual innovativeness is commonly conceptualized as a relatively stable personal tendency to embrace, generate, and adopt new ideas or technologies earlier than others. The concept originates from the Diffusion of Innovations theory, which defines innovativeness as "the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas" [15, 16]. At the behavioral level, innovativeness reflects how quickly an individual adopts new ideas compared with others within a social system [17]. Beyond early adoption, individual innovativeness is closely linked to cognitive and motivational characteristics such as curiosity, openness to experience, and a tendency toward exploration. These attributes facilitate individuals' engagement with novel technologies and uncertain environments. In organizational contexts, particularly in high-reliability sectors such as aviation, such characteristics are critical for adapting to rapidly evolving technological systems. Empirical evidence suggests that curiosity-driven exploration enhances innovative work behavior, with work engagement acting as an important mediating mechanism [18]. Similarly, positive psychological capital, comprising hope, optimism, resilience, and self-efficacy, has been shown to foster both work engagement and innovative behavior, further reinforcing individuals' capacity to adopt and utilize new technologies effectively [19]. Within aviation, where advanced automation and AI-supported decision-making systems are increasingly integrated into operational processes, individual innovativeness plays a critical role in shaping how professionals respond to technological change. Individuals who are more innovative are more inclined to explore, adopt, and develop favorable evaluations of AI-based tools, thereby forming more positive attitudes toward such systems.

2.2. Attitudes Toward AI

Attitudes toward AI refer to individuals' overall evaluative orientations toward AI systems, encompassing cognitive (beliefs), affective (emotions), and behavioral (intentions and usage tendencies) components [20, 21, 22]. Within the broader technology acceptance literature, attitudes are considered a central determinant of individuals' willingness to adopt and interact with emerging technologies, shaping both intention and actual usage behaviors. In the context of AI, attitudes are influenced by a complex interplay of perceived benefits and risks. While AI systems offer increased efficiency, decision support, and performance enhancement, they also introduce concerns related to trust, transparency, autonomy, and control. Recent studies emphasize that individuals' evaluations of AI are strongly shaped by their perceptions of uncertainty and system opacity, particularly in high-stakes environments [23, 24]. Accordingly, trust in AI and perceptions of system reliability play a critical role in fostering positive attitudes. This issue becomes especially salient in aviation, where AI is increasingly integrated into cockpit decision-support systems and operational processes. Research on AI-supported co-pilot systems and reduced crew operations highlights that AI is expected to function as an assistive tool rather than a replacement for human operators, with human oversight remaining essential for judgment, safety, and complex decision-making [24, 25]. This human-centric perspective is further reinforced by regulatory frameworks such as the European Union Aviation Safety Agency's (EASA) (2024) AI Roadmap 2.0, which emphasizes safe, transparent, and human-centered integration of AI into aviation systems. Empirical findings within aviation contexts also demonstrate that attitudes toward AI are shaped by psychological factors such as anxiety, trust, and adaptation capabilities. For instance, Ceken et al. [26] show that AI-related anxiety particularly sociotechnical concerns regarding system complexity and unintended consequences significantly influences general attitudes toward AI among student pilots. Similarly, Tuncal [27] identified moderate overall AI anxiety among aviation professionals peaking specifically in the sociotechnical sub-dimension and noted that these psychological responses can be further nuanced by demographic factors such as educational background. These findings highlight that individuals' perceptions of AI are not solely driven by technical evaluations but are also deeply embedded in their psychological responses and adaptation processes.

2.3. Relationship between Individual Innovativeness, Use of AI-Based Tools, and Attitudes Toward AI

Individual innovativeness has long been conceptualized as a fundamental personal trait shaping individuals' openness to new technologies and their willingness to experiment with novel systems. Building on the diffusion framework of Rogers [15], individual innovativeness reflects a tendency to adopt innovations earlier than others and to perceive technological change as an opportunity rather than a threat. This trait plays a particularly critical role in the context of AI, where uncertainty, perceived risk, and complexity often influence user perceptions and acceptance.

Recent empirical studies provide strong support for the role of individual innovativeness in shaping attitudes toward AI. For instance, Erciyas et al. [28] demonstrated that individual innovativeness significantly predicts positive attitudes toward AI among healthcare students, indicating that individuals with higher innovativeness levels tend to evaluate AI technologies more favorably. Similarly, Park and Woo [29] found that personal innovativeness in information technology is associated with more positive emotional and cognitive responses to AI, including higher perceived functionality and lower negative affect. These findings are further supported by Hering et al. [30], who showed that personal technological innovativeness and attitudes toward AI jointly predict AI usage behaviors, with innovativeness acting as a foundational driver of technology engagement.

In the aviation context, recent research on student pilots further highlights the importance of attitudes toward AI and related psychological factors. Ceken et al. [26] found that student pilots exhibit varying attitudes toward AI depending on factors such as AI-related anxiety and adaptation processes, emphasizing the critical role of human-centered AI integration in aviation training environments. The study demonstrated that attitudes toward AI are closely linked to how individuals perceive uncertainty and adapt to emerging technologies, reinforcing the idea that personal dispositions such as innovativeness can play a crucial role in shaping these attitudes.

Beyond direct effects, emerging research also highlights the indirect mechanisms through which innovativeness shapes AI attitudes. Usanmaz et al. [31] found that individual innovativeness mediates the relationship between employment anxiety and attitudes toward AI, suggesting that individuals who perceive themselves as more innovative are more likely to transform uncertainty into positive evaluations of AI technologies. Likewise, Ülkü et al. [32] reported that AI-related anxiety can positively influence innovative behavior through future-oriented concerns, indicating that individuals' adaptive and innovative tendencies play a crucial role in how they respond to AI-related challenges. These findings collectively suggest that innovativeness not only directly enhances positive attitudes toward AI but also functions as a psychological mechanism that transforms uncertainty into opportunity.

Another important pathway linking individual innovativeness to attitudes toward AI is the actual use of AI-based tools. According to technology acceptance perspectives, individuals who are more innovative are more likely to experiment with and adopt emerging technologies, which in turn shapes their perceptions and evaluations. Lan et al. [33] demonstrated that personal innovativeness significantly increases perceived usefulness and ease of use of AI tools, which subsequently drives behavioral intentions. In a similar vein, Marocco et al. [34] emphasized that perceived performance improvements through AI usage lead to more positive attitudes, including reduced anxiety and higher perceived utility. These findings indicate that usage experiences play a critical role in reinforcing favorable attitudes toward AI.

Within this framework, the use of AI-based tools can be conceptualized as a behavioral mechanism through which individual innovativeness translates into more positive attitudes toward AI. Individuals high in innovativeness are more likely to engage with AI tools, gain direct experience, and develop more informed and favorable evaluations. This is particularly relevant in high-stakes domains such as aviation, where exposure to AI-supported systems (e.g., decision-support tools, automation interfaces) can significantly shape trust, acceptance, and overall attitudes toward AI integration.

Taken together, the literature suggests a dual pathway: individual innovativeness directly influences attitudes toward AI, while also indirectly shaping these attitudes through increased engagement with AI-based tools. This perspective aligns with contemporary views on human–AI interaction, which emphasize the importance of both personal predispositions and experiential factors in technology acceptance.

Although previous studies have examined attitudes toward AI and related psychological factors across different populations, existing evidence remains fragmented in several respects. First, prior research has largely focused on general technology acceptance variables, AI anxiety, trust, or usage intentions, while comparatively limited attention has been given to the role of individual innovativeness as a personal characteristic shaping attitudes toward AI. Second, although several studies have explored AI perceptions in educational or healthcare contexts, empirical evidence within aviation training environments remains relatively scarce. In particular, research involving student pilots has predominantly focused on AI-related anxiety and adaptation issues rather than examining how personal characteristics and technology engagement jointly influence attitudes toward AI. Third, previous studies have generally investigated direct relationships between technological factors and AI perceptions, whereas the combined role of individual innovativeness and actual AI-based tool usage has received limited empirical attention. Addressing these gaps, the present study contributes to the literature by examining the direct effects of individual innovativeness and AI-based tool use on attitudes toward AI among student pilots, thereby extending current understanding of human-centered AI integration in aviation contexts.

Based on the theoretical arguments and empirical findings discussed above, the following hypotheses are proposed:

H1: Individual innovativeness has a positive and significant effect on attitudes toward AI.

H2: Use of AI-based tools has a positive and significant effect on attitudes toward AI.

3. Methodology

3.1. Measures

Demographic Information: A demographic information form was used to collect participants' background characteristics, including gender, age, and education level. In addition, participants' attitudes toward AI-based decision support systems in the cockpit, perceptions of AI-supported single-pilot operations, and their use of AI-based tools were assessed to provide contextual information about their experience and perceptions of AI.

Individual Innovativeness Scale: Individual innovativeness was assessed using the Individual Innovativeness Scale, developed by Hurt et al. [35] and adapted into Turkish by Kılıçer and Odabaşı [36]. The scale consists of 20 items, which are rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

General Attitudes toward AI Scale: General attitudes toward artificial intelligence were assessed using the General Attitudes toward AI Scale, developed by Schepman and Rodway [20] and adapted into Turkish by Kaya et al. [37]. The scale consists of 20 items, which are rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.2. Sample

The sample of the study consisted of student pilots receiving aviation training in Türkiye. Data were collected using a convenience sampling method through an online questionnaire. The survey was distributed via digital platforms accessible to student pilots enrolled in university aviation programs and flight training institutions. A total of 204 valid responses were obtained and included in the analysis.

3.3. Data Analysis

Data analyses were conducted using Jamovi (version 2.7.6), which is based on the lavaan package implemented in R [38]. Initially, data screening procedures were performed to examine missing values and the distributional properties of the variables. Descriptive statistics, including means, standard deviations, skewness, and kurtosis values, were calculated to assess normality. Pearson correlation analyses were conducted to explore the relationships among the study variables. The internal consistency reliability of the scales was evaluated using Cronbach's alpha coefficients, and composite scores were computed in accordance with the scale guidelines. To test the proposed research model, path analysis based on observed variables was performed. In the model, individual innovativeness was specified as the independent variable and attitudes toward artificial intelligence as the dependent variable. The use of AI-based tools was included as a control variable to account for participants' prior experience with AI technologies. Because the proposed model is just-identified (df = 0), global model fit indices were not interpreted, and the evaluation of the model was based on the significance and magnitude of the estimated path coefficients.

3.4. Ethical approval

The study was approved for ethical suitability by the International Science and Technology University Ethics Committee (Approval Date and Number: 17.07.2025/202507-02). Participation was voluntary and anonymous, and respondents were informed that their responses would be used solely for scientific purposes and treated with strict confidentiality.

4. Results

4.1. Demographic Characteristics

The demographic characteristics of the participants are presented in Table 1. The sample consisted of 204 student pilots, the majority of whom were male (78.9%), while females represented 21.1% of the sample. In terms of age distribution, participants were predominantly between 30–39 years (35.8%), followed by those aged ≤22 (27.5%) and 23–29 (26.0%), whereas a smaller proportion was aged 40 and above (10.7%). Regarding educational background, most participants held a bachelor's degree (57.8%), followed by high school or below (19.1%), postgraduate degrees (15.3%), and associate degrees (7.8%). Participants' attitudes toward AI-based decision support in the cockpit indicated a generally positive tendency, with 33.3% reporting that they support and 11.3% strongly support such systems, while 27.5% remained neutral. A smaller proportion expressed negative views (10.3% do not support; 0.5% strongly do not support). In contrast, attitudes toward AI-supported single-pilot operations were more cautious, with the majority of participants (61.3%) considering such operations not feasible, whereas 19.6% were undecided and 19.1% perceived them as feasible. Finally, the use of AI-based tools varied across the sample. While 41.2% reported occasional use and 24.5% frequent use, a notable proportion had limited or no experience with such tools (20.1% tried but rarely use; 12.3% never used; 2.0% no intention to use).

The age distribution observed in the sample reflects the heterogeneous structure of pilot training pathways rather than a conventional undergraduate student profile. Participants were recruited from both university aviation programs and authorized flight training organizations. While younger individuals often enter pilot training at the beginning of their professional careers, flight training institutions may also include older participants pursuing aviation as a second career path, engaging in late-career transitions, or undertaking private/commercial pilot conversion training. Therefore, the present sample represents a broader population of student pilots with diverse educational and training backgrounds. This characteristic should be considered when interpreting the generalizability of the findings.

Table 1. Demographic characteristics and ai-related perceptions of participants

Variables	Category	n	%
Gender	Female	43	21.1
	Male	61	78.9
Age	≤ 22	56	27.5
	23–29	53	26.0
	30–39	73	35.8
	≥ 40	22	10.7
Education Level	High school or below	39	19.1
	Associate degree	16	7.8
	Bachelor's degree	118	57.8
	Postgraduate degree	31	15.3
Attitude Toward AI-Based Decision Support in Cockpit	Strongly do not support	1	0.5
	Do not support	21	10.3
	Neutral	56	27.5
	Support	68	33.3
	Strongly support	23	11.3
Attitude Toward AI-Supported Single-Pilot Operations	Feasible	39	19.1
	Undecided	40	19.6

	Not feasible	125	61.3
Use of AI-Based Tools	Strongly no (no intention to use)	4	2.0
	No, never used	25	12.3
	Tried but rarely use	41	20.1
	Yes, occasionally use	84	41.2
	Yes, frequently use	50	24.5
Total		204	100.00

4.2. Statistical Findings

Table 2 presents the descriptive statistics, reliability coefficients, and Pearson correlation results for the study variables. The findings indicate that participants reported a moderate to high level of attitudes toward AI (AIA) (M = 64.42, SD = 11.50) and individual innovativeness (II) (M = 74.74, SD = 8.77). The distributional properties of the variables suggest acceptable normality, as skewness and kurtosis values fall within commonly recommended thresholds (|skewness| < 1, |kurtosis| < 1) [39]. Specifically, AIA exhibited slight negative skewness (−0.325) and low kurtosis (0.281), while II showed near-normal distribution characteristics (skewness = −0.024; kurtosis = 0.218). In terms of internal consistency, both scales demonstrated good reliability. The Cronbach's alpha coefficient was .875 for AIA and .820 for II, indicating satisfactory levels of internal consistency for both constructs. Pearson correlation analysis revealed a positive and statistically significant relationship between individual innovativeness and attitudes toward AI ($r = .226$, $p < .01$). This finding suggests that individuals with higher levels of innovativeness tend to exhibit more favorable attitudes toward AI.

Table 2. Descriptive statistics, skewness and kurtosis, reliability, and pearson's correlation results

Variables	AIA	II	M	SD	Skewness	Kurtosis	Cronbach's α
AIA	-	.226**	64.42	11.50	-0.325	0.281	.875
II	.226**	-	74.74	8.77	-0.024	0.218	.820

N = 204, **p < .01 (2-tailed). AIA=Artificial Intelligence Attitude; II= Individual Innovativeness

The structural model was tested using path analysis, and the results are presented in Table 3 and Figure 1. Because the proposed model is just-identified (df = 0), model fit indices are not interpreted. As shown in Table 3 and illustrated in Figure 1, both hypothesized relationships were found to be statistically significant. First, individual innovativeness had a positive and significant effect on attitudes toward AI ($\beta = 0.182$, $z = 2.82$, $p = .005$), supporting H1 [40]. Second, the use of AI-based tools also showed a positive and significant effect on attitudes toward AI ($\beta = 0.334$, $z = 5.16$, $p < .001$), supporting H2. The magnitude of this coefficient suggests a relatively stronger predictive contribution compared to individual innovativeness.

Table 3. Path analysis results

Hypothesis	Path	β	z	p	Decision
H1	Individual Innovativeness → Attitudes Toward AI	0.182	2.82	.005	Supported
H2	Use of AI-Based Tools → Attitudes Toward AI	0.334	5.16	< .001	Supported

In addition, a small yet statistically significant positive association was observed between individual innovativeness and the use of AI-based tools ($r = .13$, $p < .05$), as illustrated in Figure 1. The model explained 16% of the variance in attitudes toward AI ($R^2 = .160$), indicating a modest but meaningful level of explanatory power [39].

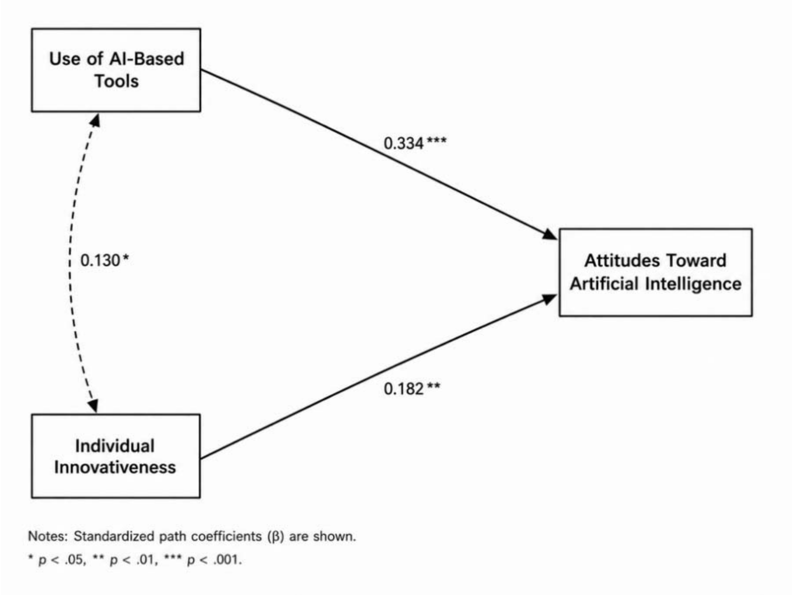

Fig 1. Path diagram

4. Discussion

The present study aimed to examine the relationships among individual innovativeness, use of AI-based tools, and attitudes toward AI within the context of student pilots. The findings provide empirical support for the proposed model and offer important insights into how both dispositional and experiential factors shape attitudes toward AI in a high-technology and safety-critical domain.

Consistent with the first hypothesis, individual innovativeness was found to have a positive and significant effect on attitudes toward AI. This finding aligns with classical innovation and technology adoption theories, which emphasize innovativeness as a key determinant of openness to new technologies [15]. More recent evidence further supports this relationship, indicating that personal technological innovativeness and attitudes toward AI jointly act as key predictors of AI usage behavior, suggesting that both general and technology-specific factors shape AI adoption [30]. In this sense, individual innovativeness can be interpreted as a foundational predisposition that enables individuals to approach AI systems with greater openness and reduced resistance.

From a human–AI interaction perspective, this finding suggests that individual differences play a critical role in shaping how users cognitively and affectively respond to intelligent systems. As highlighted in recent research, the successful integration of AI systems depends not only on interface design but also on how users perceive operational complexity and system behavior [41]. Individuals with higher innovativeness may be better equipped to cope with such complexities, thereby facilitating more effective human–AI collaboration.

The results also revealed that the use of AI-based tools has a stronger effect on attitudes toward AI than individual innovativeness. This finding highlights the importance of experiential learning in shaping AI perceptions. In line with the Technology Acceptance Model, perceived usefulness and ease of use play a critical role in shaping attitudes toward AI systems [42]. However, recent findings in the aviation context also indicate that trust in AI is not solely determined by perceived usefulness. Rather, it is influenced by factors such as transparency, explainability, and perceived system fairness. This suggests that experience with AI tools may simultaneously increase familiarity and reveal system limitations, leading to more nuanced attitudes.

The stronger impact of AI usage observed in this study is also consistent with recent research demonstrating that both innovativeness and attitudes toward AI predict actual AI usage behavior, with usage itself acting as a reinforcing mechanism that shapes future attitudes [30]. This cyclical relationship suggests that exposure to AI technologies not only reflects prior attitudes but also actively contributes to their development.

Another important dimension of the findings relates to AI-related anxiety. Prior research in aviation contexts indicates that the impact of AI anxiety on outcomes such as perceived employability may be limited, reflecting the structured and human-centered nature of the aviation sector [43]. This is consistent with the current findings, which suggest that despite potential concerns regarding AI, both innovativeness and usage contribute to more positive attitudes. Similarly, broader research indicates that anxiety related to AI can, under certain conditions, motivate adaptive and innovative responses rather than purely negative reactions [32]. This highlights the complex role of psychological factors in AI acceptance, where anxiety does not necessarily translate into resistance but may instead coexist with curiosity and openness.

The relationship between individual innovativeness and AI usage, although modest, further supports the idea that innovative individuals are more likely to engage with new technologies. This finding is consistent with research conducted in the aviation education context, which shows that aviation professionals and academics tend to exhibit openness to innovation and willingness to engage with technological change [44]. Such tendencies are particularly important in sectors characterized by rapid technological advancement.

From a broader aviation and mobility perspective, attitudes toward emerging technologies are known to vary across individuals and groups, with distinct clusters ranging from early adopters to skeptics [45]. This diversity in attitudes suggests that AI acceptance cannot be treated as a uniform phenomenon and highlights the importance of considering individual differences such as innovativeness and experience when examining technology adoption.

In addition, the findings should be interpreted in light of ongoing transformations in aviation systems and training environments. Despite the increasing emphasis on AI integration in aviation operations, recent studies indicate that current educational programs may not sufficiently equip students with the necessary AI-related competencies [46]. This gap underscores the importance of not only developing technical skills but also fostering positive attitudes and readiness for human–AI collaboration among future aviation professionals.

5. Conclusion

This study provides empirical evidence that both individual innovativeness and the use of AI-based tools play significant roles in shaping attitudes toward artificial intelligence among student pilots. The findings indicate that while individual innovativeness contributes to a general openness and predisposition toward emerging technologies, direct interaction with AI systems emerges as a relatively stronger determinant of positive attitudes. This highlights the critical role of experiential learning and hands-on engagement in fostering favorable perceptions of AI. Within the aviation context, where human–AI collaboration is rapidly evolving and becoming integral to operational environments, these findings carry important implications. The increasing integration of AI-driven decision-support systems, automation interfaces, and intelligent cockpit technologies necessitates not only technical proficiency but also psychological readiness, trust, and adaptability among future aviation professionals. In this regard, the results emphasize that exposure to AI applications during training processes can enhance familiarity, reduce uncertainty, and ultimately facilitate acceptance. From a theoretical perspective, the study contributes to the growing body of literature on technology acceptance by integrating both dispositional (individual innovativeness) and behavioral (technology use) dimensions within a human-centered AI framework. This dual perspective offers a more comprehensive understanding of how attitudes toward AI are formed, particularly in high-reliability domains such as aviation, where safety, trust, and decision-making are paramount. The findings suggest that successful AI adoption is not solely driven by individual characteristics or system features, but rather by the dynamic interaction between users and technologies. Accordingly, fostering positive attitudes toward AI requires not only selecting individuals with higher innovative tendencies but also designing training environments that promote meaningful engagement with AI systems. Furthermore, these results highlight the importance of embedding AI literacy, transparency, and trust-building mechanisms into aviation education and training programs to support the long-term sustainability of human–AI collaboration. These insights underline the importance of aligning technological development with human-centered design principles to ensure the effective and sustainable integration of AI in aviation and beyond.

Practical Implications and Limitations: The findings suggest several practical implications for aviation training institutions and industry stakeholders aiming to enhance human-AI integration. Given that the use of AI-based tools emerged as a stronger predictor of attitudes than individual innovativeness, training programs should prioritize hands-on, scenario-based AI applications to foster familiarity, perceived usefulness, and acceptance consistent with both classical and recent technology acceptance research [47, 48, 49, 50]. Additionally, integrating elements of trust, transparency, and explainability into training environments is essential, as these factors play a critical role in shaping user acceptance in safety-critical domains [42]. Educational practices should also support the development of individual innovativeness and address AI-related anxiety through structured exposure and guided interaction [15, 20, 43]. Finally, given the growing gap between industry needs and current training content, incorporating AI literacy and human–AI collaboration skills into aviation curricula is crucial for preparing future professionals for technology-intensive operational environments [46]. This study has several limitations that should be considered when interpreting the findings. First, the cross-sectional design limits the ability to draw causal conclusions, as the relationships reflect associations at a single point in time. Second, the use of a convenience sample consisting of student pilots in Türkiye may restrict the generalizability of the results to other populations and aviation contexts. Third, the reliance on self-reported data introduces the possibility of common method bias and response-related biases. Finally, although validated scales were employed, the analysis was conducted using composite scores rather than latent constructs, which does not account for measurement error at the item level.

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Research Article

The macroeconomic impact of residential construction on national productivity

Mustafa Arıcan*[1a], Soner Şeker[2b]

[1] *Independent Researcher, Ankara, Türkiye*
[2] *Department of Civil Engineering, Faculty of Engineering and Natural Sciences, Uşak University, Uşak, Türkiye*

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Abstract

While housing development generates substantial output and employment multipliers that accelerate domestic monetary velocity, its hyper-financialization introduces severe macroeconomic vulnerabilities. The economic impact of housing construction is characterized by high multipliers and complex resource allocations. Quantifying these effects reveals that in specific contexts, such as Australia, every $1 million in residential output generates $2.9 million in total economic output and sustains nine jobs. While housing acts as a significant catalyst, the sector faces a global productivity paradox and substantial risks of resource misallocation. For instance, China exhibits a 22.4% vacancy rate, highlighting potential inefficiencies in large-scale residential development. Furthermore, housing construction can exert a crowding-out effect on industrial investment, potentially hindering broader manufacturing growth. Despite these challenges, targeted investments in affordable housing demonstrate significant social value, with Social Return on Investment (SROI) ratios reaching up to 1 to 3.22. This research suggests that while residential development is a powerful economic engine, its efficacy depends on balancing immediate output with long-term industrial health and occupancy stability. Strategic planning is required to mitigate the productivity gap and ensure that the substantial economic multipliers of housing construction translate into sustainable national growth without depleting resources from other vital sectors.

1. Introduction

Housing represents the largest asset owned by most households globally and serves as a primary vehicle for wealth accumulation, particularly within the middle class [1]. Beyond individual wealth parameters, housing plays a transformative and often volatile role in shaping aggregate macroeconomic outcomes. Because homeownership is simultaneously the largest source of domestic debt and private wealth, the housing sector is central to understanding the genesis and propagation of boom-and-bust economic cycles [2]. Currently, the macroeconomic pressures surrounding residential real estate are unprecedented; real global house prices sit approximately 20 percent above their levels following the 2008 global financial crisis, and demographic projections indicate that 3 billion people will require access to adequate, newly constructed housing by 2030 [3]. Consequently, housing operates within a highly unique dual capacity in modern economic theory, it is an absolute biological and social necessity required for labor reproduction and stability, while simultaneously functioning as the most heavily financialized asset class anchoring the global banking system.

*Corresponding author: mustafarican15@gmail.com
[a]orcid.org/0000-0002-0716-2729, [b]orcid.org/0000-0002-7632-9713
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This dual nature generates a profound debate among central bankers, macroeconomic policymakers, and urban economists regarding the optimal allocation of a nation's capital. The core research question addressed in this article is whether aggregate capital directed into residential construction acts as a sustainable economic stimulant, or whether it ultimately devolves into a parasitic drain on national productivity. In traditional financial literature, investments in advanced manufacturing, technological research, or commercial infrastructure are unequivocally classified as "productive assets" because they generate compounding revenue, continuous innovation, and intrinsic value independent of speculative market pricing [4]. The macroeconomic classification of housing construction, however, is heavily contested. While immediate Keynesian multipliers suggest construction drives localized employment, recent empirical evidence indicates that persistent, rapid increases in real house prices, and the subsequent over-allocation of capital to residential construction, can negatively impact long-term labor productivity growth across advanced economies [5]. Furthermore, excessive housing booms have been linked to severe resource misallocation at the industry level [6]. Therefore, this article seeks to systematically delineate the precise conditions under which building houses creates compounding economic surplus versus when it generates structural macroeconomic vulnerability.

To rigorously evaluate the opposing dynamics of residential construction, this article synthesizes a multifaceted quantitative methodology. The scope of the analysis transcends standard GDP growth accounting by integrating cross-country econometric data, input-output sector multipliers, and advanced corporate valuation metrics such as Economic Value Added (EVA). Central to this methodology is the application of recent theoretical frameworks that quantify a "sufficient statistic" to measure the net effect of housing prices on real investment [7]. This framework isolates the tension between the "collateral channel," where rising real estate values relax corporate borrowing constraints to spur industrial investment, and the "crowding-out channel," where inflated land and construction costs drain capital away from productive non-housing sectors [6,7]. By applying this framework alongside structural vector autoregression (SVAR) analyses and difference-in-differences approaches across divergent markets, from the advanced economies of the European Union to the construction-led growth models of emerging markets, this article provides a comprehensive assessment of how institutional and regulatory environments dictate the ultimate economic utility of residential construction [8].

2. Theoretical Framework of Housing as Economic Capital

To accurately evaluate the macroeconomic utility of residential construction, it is first necessary to establish the epistemological classification of housing within modern economic theory. Assets are fundamentally bifurcated into productive and non-productive categories. A productive asset is defined as an investment that generates continuous income or appreciates in intrinsic value through its own economic utility, such as commercial real estate, equities, or industrial machinery [4]. Conversely, non-productive assets, such as gold or certain speculative commodities, generate no independent yield; their value relies entirely on market sentiment, fear, and capital appreciation driven by subsequent buyers [4].

In this context, residential real estate stands as a clearly productive asset. Conventional economic principles suggest that food and housing are the two most critical requirements for sustaining a healthy economy and a functional workforce. From an investment perspective, housing generates wealth through two distinct channels: the growth of its market value and the production of ongoing revenue. While landlords collect this revenue through direct rental payments, homeowners receive what is known as 'imputed rent' a theoretical financial benefit they essentially pay themselves for the continued use and utility of their own residence [9].

Furthermore, behavioral economic surveys conducted by the Federal Reserve Bank of New York reveal that households view housing as an optimal investment not merely for its financial return, but because it functions as an accessible source of leverage, acts as a commitment device for forced saving through mortgage amortization, and provides a critical hedge against rising localized housing costs [1]. Therefore, the foundational act of building a home creates a durably productive asset that yields societal and individual dividends for decades, directly enhancing the stability and efficacy of the national workforce.

2.1. The Financialization of Real Estate

While the individual utility of housing is well established, its aggregate macroeconomic impact cannot be fully comprehended without examining its deep integration into the modern financial architecture. Over the past century, global real estate has undergone a profound structural transformation characterized by intense financialization. Historically, banking institutions engaged in a highly diverse array of commercial and industrial lending; today, however, most banks across the developed and developing world function primarily as mortgage creation vehicles [10].

This phenomenon, frequently termed "The Great Mortgaging" within economic literature, has inextricably linked the stability of the global banking sector to the underlying price of land and residential property [10]. Because homeownership represents the largest single source of both private wealth and household debt, the housing sector serves as the central conduit through which boom-and-bust economic cycles are generated and propagated across the broader economy [2].

When land and housing prices rise, the collateral base of the economy expands. This dynamic fundamentally alters credit availability, loosening borrowing constraints not just for households, but for corporate entities that hold real estate on their balance sheets [10]. However, this deep financialization introduces systemic vulnerabilities. As housing evolves into a heavily traded financial commodity, its price dynamics often detach from the organic demographic demand for shelter, driven instead by mortgage credit availability and speculative investment flows. The macroeconomic stability of a nation thus becomes deeply dependent on maintaining a delicate balance between utilizing real estate as productive collateral and preventing the sector from morphing into a speculative vacuum that distorts the national allocation of capital.

3. Quantifying Output and Employment Multipliers

To accurately measure the macroeconomic stimulus provided by residential construction, economists rely heavily on input-output multipliers. These multipliers capture the extensive horizontal and vertical linkages the construction sector maintains with the broader economy [11,12]. Vertical linkages refer to the deep supply chains required to source building materials, encompassing raw material extraction, manufacturing, and logistics, while horizontal linkages involve complementary sectors such as financial services, real estate brokerage, and legal underwriting [12].

Empirical data confirms that due to these interdependencies, residential construction generates some of the highest economic multipliers of any sector. An exhaustive analysis conducted by the National Housing Finance and Investment Corporation (NHFIC) in Australia demonstrated that the residential building construction industry possesses the second-largest economic multiplier among all 114 industries within the national economy [13]. Specifically, the NHFIC determined that every $1 million of output in residential building construction supports approximately $2.9 million in total industry output and consumption across the broader economy [13]. The widespread economic impact and employment multipliers generated by housing construction are summarized in Table 1 to illustrate the sector's place in the national economy as adapted from [11].

Table 1: The Keynesian Stimulus and Domestic Multiplier Effects of Residential Construction

Impact Category	Key Input / Metric	Multiplier Effect / Outcome	Explanation and Macroeconomic Mechanism
Economic Output	$1 Million of Output	$2.9 Million Total Output	Driven by high interdependencies, residential construction generates some of the highest economic multipliers, supporting total industry output and consumption across the broader economy.
Job Creation (Investment-Driven)	$1 Million of Output	9 Jobs Supported	The sector acts as a vital engine for employment generation, supporting robust indirect and direct employment across the broader economy.
Job Creation (Unit-Driven)	1 Average New Home	3 Full-Time Equivalent Jobs	The construction of a single physical structure directly translates into strong labor demand, supporting full-time equivalent employment.
Velocity of Domestic Capital	Localized Supply Chains	Minimal Import Leakage, High Velocity of Money	Because structures cannot be efficiently imported as finished products, capital predominantly circulates domestically, supercharging recovery efforts without worsening national trade deficits.
Labor Intensity by Developmental Stage	Capital vs. Labor Distribution	Poverty Alleviation in Emerging Markets	While advanced economies rely on mechanization, labor-intensive methods in developing economies act as a critical sponge for unskilled labor and a mechanism for wealth distribution.

3.1. Labor Intensity and Job Creation

Beyond gross output, the construction sector is a vital engine for employment generation, accounting for roughly 5 percent of annual gross domestic product in economies like Australia and directly employing hundreds of thousands of individuals [13]. The employment multiplier effect is particularly robust; for every $1 million of economic output generated by the residential construction industry, nine jobs are supported across the broader economy, meaning the construction of a single average new home supports three full-time equivalent jobs [13].

However, the nature of this labor intensity varies significantly depending on a nation's developmental stage. In advanced economies, high labor costs have driven the industry toward equipment-intensive technologies and mechanization [14]. Conversely, in developing, capital-scarce, and labor-abundant economies, housing construction relies heavily on labor-intensive methods, acting as a critical sponge for unskilled and semi-skilled workers [15]. Research demonstrates that with appropriate managerial oversight, these labor-intensive construction programs are highly competitive in terms of productivity and quality with mechanized methods, providing essential wealth distribution and poverty alleviation mechanisms in emerging markets [15].

3.2. Velocity of Domestic Capital

The macroeconomic efficacy of the construction multiplier is further amplified by the sector's geographic independence and localized market scale [12]. Unlike manufactured consumer goods, residential structures cannot be efficiently imported as finished products. Consequently, the capital expended on housing construction, from paying local subcontractors to purchasing heavy building materials, predominantly circulates within domestic borders.

This reliance on localized supply chains minimizes macroeconomic import leakage, ensuring that the initial investment retains a high velocity of money as it cascades through the regional economy [12]. Especially during periods of economic downturn characterized by high spare capacity, this localized spending creates positive payroll effects and supercharges recovery efforts without disproportionately worsening national trade deficits [12,13].

4. The Collateral and Crowding Out Channels

The macroeconomic impact of residential construction and the ensuing fluctuations in real estate prices are transmitted to the broader economy through two primary, opposing mechanisms, the first of which is the collateral channel. The collateral effect represents a positive economic externality wherein an increase in real estate prices raises the value of a firm's existing real estate assets [7]. Because physical property is the most widely accepted form of collateral within the global banking system, this appreciation directly relaxes a firm's borrowing constraints, enabling it to secure additional capital to invest in its own productive processes, technological upgrades, and labor expansion [7]. This theoretical mechanism is robustly supported by empirical spatial panel data models from Chinese urban centers, which demonstrate a significant "crowding-in" effect where rising house prices lead to greater manufacturing concentration and industrial capital expansion due to the enhanced collateral values held by local firms [16]. In this scenario, strong residential construction markets act as a financial catalyst for broader industrial growth by enhancing corporate liquidity. Whether construction activities are a productive economic engine or a systemic risk leading to resource waste can be analyzed using the conditional value matrix presented in Table 2 as conceptualized based on [17–19].

Table 2: The Conditional Value Matrix for distinguishing economic stimulants from systemic risks

Value Creation (Economic Engine)	Resource Waste (Systemic Risk)
Driven by genuine demographic shelter deficits.	Decoupled from demographics to meet speculative GDP targets.
Triggers the Collateral Channel (crowding-in productive investment).	Triggers the Crowding-Out Channel (starving commercial credit).
Maintains positive Economic Value Added (EVA) corporate structures.	Relies entirely on artificially suppressed interest rates.
Yields high SROI, pre-emptively reducing state emergency costs.	Results in physical 'Ghost Cities' and sovereign banking collapse.

4.1. The Crowding Out Effect

Conversely, the crowding-out effect introduces a severe negative externality that can transform a housing boom into a parasitic drain on national productivity. While rising prices relax constraints for existing property owners, they simultaneously inflate the cost of acquiring new real estate assets [7]. For growing firms that require additional land or facilities to expand physical operations, these inflated real estate acquisition costs drain capital that would otherwise be allocated to real, productive investments such as machinery or research and development [7].

This dynamic is particularly detrimental to innovative firms with limited existing tangible assets. Recent empirical analysis utilizing detailed firm-level data from 2000 to 2023 in Canada reveals that persistent house price increases actively dampen investment for firms with fewer tangible assets, while stimulating those with substantial existing property portfolios [6]. Consequently, while aggregate output might initially appear stable during a construction boom, industries heavily reliant on acquiring new physical footprints experience significant resource misallocation, ultimately stifling long-term macroeconomic innovation and productivity [6].

4.2. The Sufficient Statistic Framework

To mathematically resolve the tension between these opposing channels and determine whether a regional housing market is stimulating or cannibalizing industrial investment, economists utilize an advanced quantitative framework that generates a "sufficient statistic" [7]. This model measures the net effect of housing prices on real aggregate investment by analyzing observable firm-level quantities [7]. For each firm within a region, the framework calculates a specific metric by multiplying its marginal productivity of capital by factors that increase with the firm's new real estate purchases and decrease with both its existing property inventory and its permissible loan-to-value ratio [7].

When these individual firm values are aggregated, the resulting sum indicates which macroeconomic force is dictating the broader economy. If the sum is positive, the crowding-out effect dominates, indicating that real estate has become too expensive, capital is being misallocated, and total economic surplus is being actively destroyed [7]. In such parasitic scenarios, the framework suggests policymakers must implement expansionary supply-side policies, such as targeted construction subsidies, combined with contractionary demand-side policies, like taxes on speculative real estate purchases, to correct the imbalance [7]. The severity of this crowding-out is further exacerbated if regional banks are capital-constrained; smaller banks may shift their lending portfolios heavily toward real estate to capitalize on rising collateral values, thereby deliberately starving non-housing commercial sectors of vital credit [7].

5. Opportunity Costs and the Construction Productivity Paradox

The macroeconomic decision to funnel domestic savings and credit into residential real estate inherently involves massive opportunity costs. Historically, sustainable economic development and transition to high-income status have been heavily correlated with industrialization and the expansion of the manufacturing sector. Empirical analyses of global growth episodes over the last half-century demonstrate that the manufacturing sector drove two-thirds of all significant economic growth periods, providing longer-lasting expansions and greater per capita income generation than service or construction-led growth [20].

Therefore, when a nation over-indexes its capital allocation into residential housing, it risks starving advanced manufacturing and technological sectors of vital resources. The magnitude of this opportunity cost is starkly visible when examining recent industrial policy shifts in advanced economies. In the United States, targeted federal legislation, such as the CHIPS Act and the Inflation Reduction Act, successfully doubled real manufacturing construction spending between 2021 and 2023, aggressively funneling capital into highly productive semiconductor and electronics fabrication facilities [21]. While this specific industrial boom did not strictly crowd out other private investments due to the exceptional depth of U.S. capital markets [21], it highlights the sheer volume of capital required to build technologically compounding infrastructure. In developing or transition economies with scarce capital, directing these immense financial flows toward speculative residential builds actively deprives the industrial base of the physical plants necessary for global competitiveness.

5.1. The Global Productivity Drag

Compounding the macroeconomic opportunity cost is the severe internal inefficiency of the construction sector itself. If an economy relies on building housing as an aggregate stimulus, it is effectively funneling national wealth into an industry experiencing a profound and enduring productivity paradox. According to comprehensive industry data tracking tens of thousands of large-scale global projects, construction productivity has effectively stagnated for decades [22].

Between the years 2000 and 2022, the global construction industry's aggregate productivity improved by a mere 10 percent, translating to an annualized compound growth rate of just 0.4 percent [22] (Figure 1). To place this structural failure in a macroeconomic context, the broader global economy achieved a 50 percent improvement in productivity during the same period, while the manufacturing sector achieved a staggering 90 percent improvement, or a 3 percent annual growth rate [22].

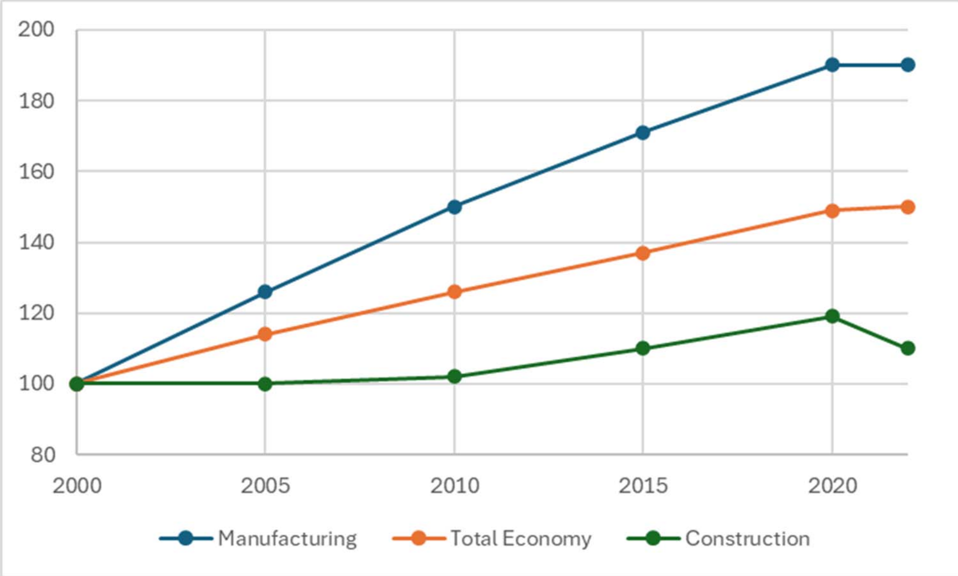

Fig. 1: Real gross value added per hour worked (global). Adapted from [23]

This productivity drag is driven by fragmented supply chains, thin profit margins, and a systemic under-investment in digital modernization. Construction firms historically allocate less than 1 percent of their revenues to information technology and operational modernization, compared to over 3 percent in advanced manufacturing sectors like aerospace and automotive [22]. Because sector productivity is flatlining, construction costs persistently outpace general macroeconomic inflation, rising by an additional 1 to 3 percent annually, acting as a direct, compounding tax on national capital formation [22].

5.2. Economic Value Added

To determine if large-scale housing investments truly contribute to national economic growth, modern financial analysts prioritize Economic Value Added (EVA) over conventional measures like Return on Equity (ROE) or Return on Assets (ROA). As a rigorous performance indicator, EVA identifies genuine economic profit by subtracting the comprehensive cost of all financing-including both debt and equity from the net operating profit remaining after taxes. This approach ensures that a project is only considered value-adding if its returns exceed the total cost of the capital used to fund it, distinguishing real economic engines from mere resource waste [24,25].

The application of EVA exposes how artificially cheap credit can mask the destruction of wealth in real estate development. A prime macroeconomic example occurred in China, where the State-Owned Assets Supervision and Administration Commission (SASAC) historically utilized ROE to evaluate the performance of state-owned enterprises (SOEs) [26]. This metric perversely incentivized managers to overspend on massive, low-return real estate and infrastructure projects simply because bank loans were artificially cheap, even when the actual returns on these projects were lower than the interest on the debt. Recognizing this massive resource waste, SASAC shifted its primary evaluation metric to EVA in 2010 to force capital discipline, ensuring that heavy capital expenditures in construction genuinely exceeded the opportunity cost of the funds deployed. Ultimately, if construction firms operate with a negative EVA, the physical act of building houses ceases to be an economic stimulant and instead systematically destroys aggregate national wealth [24–26].

6. Divergent National Paradigms and Macroeconomic Outcomes

To empirically validate the theoretical mechanisms of the collateral and crowding-out channels, it is necessary to examine nations that have explicitly adopted construction-led growth models. While aggressive residential construction can effectively pull an economy out of a localized recession, relying on real estate development as a primary, long-term engine for macroeconomic expansion routinely generates severe structural vulnerabilities. The following sub-sections analyze three distinct global paradigms, demonstrating how the over-allocation of capital into housing manifests in emerging markets, state-directed economies, and advanced financial systems. Analysis of different national paradigms demonstrates that the macroeconomic impact of housing should be assessed not only through its direct contribution to GDP but also through the social externalities ecosystem as shown in Figure 2 based on data from [29, 30].

Fig. 2: Monetizing externalities with SROI

When SROI methodologies are empirically applied to affordable residential housing, the net positive macroeconomic value decisively outpaces the resources expended.

6.1. Structural Vulnerabilities in Turkey

The Republic of Türkiye provides a highly documented empirical case study regarding the limitations and risks of a construction-centric economic paradigm. Following the 2001 financial crisis, Turkey experienced a period of rapid economic expansion, heavily utilizing the construction sector to drive employment and output. However, a rigorous econometric analysis of the Turkish economy utilizing Vector Autoregression (VAR) models and Granger causality tests spanning from 1998 to 2014 reveals a problematic structural evolution [27]. For the majority of this period, real GDP growth preceded construction activity, indicating that housing was a follower of organic macroeconomic fluctuations [27].

A profound structural break occurred between 2010 and 2014, during which the direction of causality entirely reversed; expansion in the construction sector began to artificially drive a 9 percent real GDP growth rate [27]. This reversal was engineered by a highly accommodative monetary environment where average real interest rates plummeted to a mere 0.14 percent, sparking a massive credit-fueled building boom [27].

While this generated immense short-term output, it structurally compromised the Turkish economy. The building sector accounts for more than 35 percent of the country's total final energy consumption, heavily exacerbating Turkey's reliance on imported natural gas and coal, thereby exposing the national budget to global energy price shocks [28,29]. Furthermore, the rapid, under-regulated nature of this "neoliberal urbanism", which fostered an incestuous cycle between state-led developers and private contractors, resulted in catastrophic human and economic costs during the 2023 earthquakes, which claimed over 50,000 lives and destroyed 1.9 million housing units [30,31]. Despite these vulnerabilities, the Turkish economy remains deeply tied to this sector, with construction output hitting a record high index of 151.2 in late 2025 and driving a 3.6 percent GDP growth rate, prompting the International Monetary Fund to urge tighter monetary and fiscal policies to transition the economy toward sustainable, high-productivity sectors [32–34].

6.2. Speculative Excess and Dead-Weight Loss in China

If Turkey illustrates the regulatory and inflationary limits of a construction-led growth strategy, China demonstrates the absolute physical and environmental limits of utilizing housing as a synthetic macroeconomic stimulus. The Chinese urban real estate market has historically served as a foundational pillar of the national economy, accounting for approximately 15 percent of the country's GDP [35]. To sustain aggressive, predetermined GDP growth targets, particularly following the 2008 global financial crisis, Chinese local governments engaged in debt-fueled, land-centered urbanization that became entirely decoupled from organic demographic demand [36].

Because real estate was perceived by the Chinese middle class as the safest, preferred investment vehicle, immense capital flows bypassed equity markets and productive industrial investments, flooding directly into property speculation [37]. The direct macroeconomic result was the proliferation of ghost cities, vast, newly built urban metropolises designed to accommodate future growth that remain almost entirely uninhabited [37]. By 2013, researchers estimated that approximately 49 million newly constructed residential units sat empty, representing a staggering national urban vacancy rate of 22.4 percent, with specific developments reporting vacancy rates as high as 90 percent [38].

From a strict macroeconomic perspective, utilizing labor and materials to construct homes that are never inhabited represents an unprecedented dead-weight economic loss. It generates immense negative externalities, including massive local government debt pressure, property devaluation, and severe resource exhaustion [39]. Globally, the construction industry consumes an average of 30 percent of all fresh water; pumping these critical resources, alongside millions of tons of steel and cement, into vacant assets represents an irrecoverable environmental and material loss that actively drags down aggregate economic efficiency [40].

6.3. Sovereign Contagion in the European Periphery

The systemic risks of construction-led financial distortion are equally prevalent in advanced Western economies. Prior to the 2008 global financial crisis, Spain and Ireland developed the most housing-centric economies within the entire OECD [41]. The integration of these periphery nations into the Eurozone drastically lowered their domestic borrowing costs, resulting in unprecedented inflows of mobile foreign capital [41,42]. Instead of this liquidity flowing into highly productive, tradable sectors such as export manufacturing, it overwhelmingly flooded the residential real estate market, driving home price growth to roughly 10 percent year-over-year in 2006go[41,43].

This hyper-financialization created a profound fiscal illusion. The construction boom generated massive, immediate tax revenues, which prompted governments to engage in populist fiscal policies and aggressive tax cuts that severely eroded their structural fiscal bases [41]. In Ireland, the tax system was altered so drastically that by 2008, approximately 40 percent of employees paid absolutely no income tax, a structural deficit masked entirely by the extraordinary, yet temporary, revenue flows generated by transactional construction activity [41,44].

When the housing bubble inevitably burst, the macroeconomic spillover effects transmitted through the credit market were devastating. The net worth of domestic banks heavily exposed to the housing bubble collapsed, severely contracting the credit available to non-housing firms and plunging both countries into protracted sovereign debt crises [42]. The Spanish and Irish case studies empirically illustrate that unchecked residential construction booms distort a nation's banking risk profile, create false fiscal security, and ultimately result in massive wealth destruction when asset prices correct.

7. Monetizing Social Externalities through SROI

Traditional macroeconomic metrics, such as gross domestic product (GDP) contributions or the previously discussed Economic Value Added (EVA), are strictly confined to direct financial flows, material expenditures, and market-clearing prices. Consequently, they structurally fail to capture the profound public health, environmental, and social externalities generated by the provision of secure shelter. To comprehensively determine whether the construction of new housing creates more aggregate value than it expends, macroeconomic analysis must look beyond pure financial returns and incorporate alternative econometric methodologies, most notably the Social Return on Investment (SROI) framework.

SROI is an advanced metric adapted from traditional return on investment (ROI) that explicitly identifies, measures, and monetizes the social, environmental, and broader economic gains that result from a specific capital investment [19]. By translating traditionally intangible human outcomes, such as psychological well-being, neighborhood safety, increased individual independence, and generational wealth preservation, into a tangible dollar value, SROI utilizes a benefit-cost ratio to communicate holistic value creation [19,45]. This allows policymakers to accurately weigh the true, society-wide dividends of housing construction against the initial physical and financial costs.

7.1. Valuing Affordable Development

When SROI methodologies are empirically applied to affordable and dedicated-site supportive residential housing, the net-positive macroeconomic value of construction becomes undeniably apparent. A detailed SROI evaluation of dedicated-site supportive housing in British Columbia, Canada, specifically analyzing facilities such as the Cardington Apartments in Kelowna, demonstrates that the construction and ongoing operation of such residential units generates massive, cross-sectoral savings for both the state and the local municipality [46]. The preventative impact of strategic housing projects on the public in terms of urgent health and justice costs, and their net social return per investment, are presented comparatively in Figure 3 based on data from [29, 30].

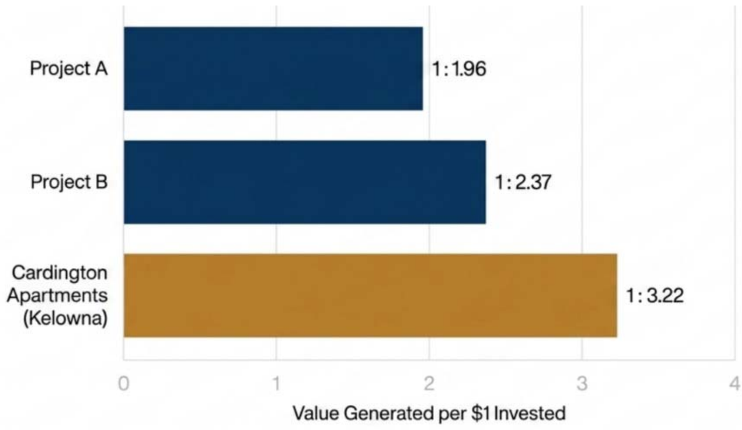

Fig. 3: Affordable housing construction pre-emptively eliminates massive public expenditures

Providing newly constructed, stable housing to vulnerable populations directly leads to quantifiable, monetized reductions in the utilization of expensive emergency medical services (such as ambulances and emergency room visits), long-term hospital stays, and reliance on temporary homeless shelters [46]. Simultaneously, secure housing significantly decreases resident involvement in the criminal justice system, thereby lowering state policing and incarceration costs, while increasing local economic activity through resident spending and improved neighborhood quality [46].

Quantitative data from BC Housing evaluating multiple supportive housing projects, with initial capital investments ranging from $1.7 million to $13.2 million, revealed highly positive SROI ratios ranging from 1:1.96 up to 1:3.22 [45]. In the most efficient developments, for every single dollar of capital investment expended on purchasing, renovating, or constructing these residential units, society reaped over three dollars in measurable social and economic value [45].

Similar independent SROI analyses conducted by organizations such as Inn from the Cold and Rebuilding Together corroborate these findings, demonstrating that strategic investments in housing yield highly monetized benefits in physical health, emotional well-being, and poverty alleviation [19,47]. Crucially, economic analysts note that these high SROI ratios still likely represent a conservative estimate of total value, as many compounding long-term impacts, such as the intergenerational life skills gained through housing stability, cannot be perfectly monetized into the future [46]. Therefore, when residential construction is strictly aligned with genuine demographic deficits and utilized to house a population, its aggregate long-term value creation decisively outpaces the resources it expends.

8. Conclusion and Policy Implications

This study has systematically evaluated the macroeconomic dichotomy of residential construction, investigating whether it functions as a sustainable economic stimulant or a parasitic drain on national productivity. The novelty of this research lies in its synthesis of the collateral and crowding-out channels with advanced corporate valuation metrics across divergent global development paradigms. Furthermore, the methodological novelty of this paper is significantly enhanced by incorporating primary empirical data, localized municipal reports, and published literature. Main conclusions of the study may be listed as follows:

- Residential construction acts as a potent, highly localized economic stimulant when an economy operates below full capacity and possesses a genuine demographic deficit of shelter.
- Through deep vertical and horizontal supply chain linkages, the construction sector generates exceptional output and employment multipliers that accelerate domestic monetary velocity and actively minimize macroeconomic import leakage.
- When real estate values appreciate organically alongside wage growth, the collateral channel is activated, allowing commercial firms to leverage physical property to secure credit and crowd-in broader industrial and technological investments.
- Conversely, when housing markets transition into speculative financial instruments decoupled from demographic realities, the crowding-out channel dominates aggregate economic activity.
- This crowding-out effect actively drains vital financial capital and credit away from innovative, high-yield manufacturing and tradable sectors, stifling long-term national competitiveness.
- The global construction industry suffers from a severe, decades-long productivity stagnation driven by fragmented supply chains, thin profit margins, and a chronic under-investment in digital modernization.
- Because of this enduring productivity paradox, over-indexing national capital into the physical construction of housing inherently acts as a compounding tax on aggregate economic efficiency.
- Debt-fueled, construction-led growth models, while highly capable of temporarily inflating gross domestic product and generating immediate tax revenues, routinely mask and generate severe structural vulnerabilities.
- These localized vulnerabilities rapidly scale into systemic threats, manifesting as massive environmental dead-weight losses, sovereign banking contagion, and the severe erosion of a nation's structural fiscal base when over-leveraged asset prices inevitably correct.
- Targeted capital deployment into affordable and dedicated-site supportive housing circumvents speculative financial waste and generates profound, measurable societal dividends.
- These affordable housing developments yield exceptional Social Return on Investment ratios by preemptively reducing downstream state expenditures on emergency healthcare, temporary welfare, and criminal justice systems.

Ultimately, the macroeconomic impact of building houses is not an absolute constant but a highly conditional outcome dictated by regulatory frameworks, financial oversight, and capital discipline. When aligned with genuine human necessity and evaluated through stringent, value-based metrics like Economic Value Added and Social Return on Investment, residential construction is a fundamentally productive endeavor that stabilizes the labor force. However, without aggressive macroprudential regulations, comprehensive zoning reforms to unlock land, and targeted demand-side interventions to curb speculation, unchecked housing booms risk transforming from vital engines of domestic growth into profound systemic liabilities.

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