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From AI to action: Exploring the mediating role of ethical decision-making in the generative AI-procrastination relationship

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Abstract

This study explores the mediating role of ethical decision-making in the relationship between generative AI usage and academic procrastination among university students, addressing gaps in understanding how moral reasoning influences AI-human behavioral interactions. A cross-sectional survey was conducted with 727 participants from Al-Azhar University, Egypt, and the College of Basic Education, Public Authority for Applied Education and Training, Kuwait, with 609 females (83.8%) and 118 males (16.2%) across diverse educational backgrounds (doctoral, master's, graduate diploma levels, and undergraduate levels). Results revealed significant relationships among all variables. Generative AI usage negatively affected academic procrastination ($\beta = -.208$, $p < .001$) and positively affected ethical decision-making ($\beta = .118$, $p < .001$). Ethical decision-making negatively affected procrastination ($\beta = -.159$, $p < .001$). The total effect of generative AI usage on procrastination was significant ($\beta = -.227$, $p < .001$). The mediation analysis demonstrated that ethical decision-making partially mediates the AI-procrastination relationship, with a significant indirect effect ($\beta = -.0188$, 95% CI [-.0126, -.0022]) representing 8.27% of the total effect. Despite common assumptions, generative AI usage is linked to reduced academic procrastination, with ethical decision-making acting as a modest mediator. Moral reasoning is one pathway through which AI tools influence student behavior, while other mechanisms account for the majority of the effect. Educational institutions should develop AI literacy programs that promote technical competencies and ethical reasoning, rather than restrictive policies, to enhance academic productivity and promote responsible AI integration strategies.

Keywords: Academic procrastination, Ethical decision-making, Generative artificial intelligence, Higher education, Human-AI interaction.

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1. Introduction

The rapid proliferation of generative artificial intelligence tools, particularly ChatGPT, has fundamentally transformed educational and professional environments, creating unprecedented shifts in how individuals approach academic and workplace tasks. In higher education settings, students have extensively embraced these technologies for academic writing, literature reviews, and personalized tutoring support, while educators increasingly integrate AI tools for lesson planning, assessment development, and professional development activities [1, 2]. This widespread adoption reflects generally favorable attitudes among students, who particularly value AI's utility in reducing academic burdens and enhancing motivational engagement [3, 4]. However, the dynamics of AI adoption reveal complexities that extend beyond initial enthusiasm, with longitudinal studies indicating potential usage decline over time due to evolving trust perceptions and growing concerns about technological dependence [5].

The influence of AI adoption extends significantly into professional contexts, where academic staff report that ChatGPT adoption substantially influences performance outcomes while simultaneously generating increased stress levels and ongoing debates regarding ethical implementation standards [6]. Similarly, professional environments demonstrate a growing integration of AI tools, although adoption rates remain contingent upon perceived benefits, institutional support structures, and comprehensive policy frameworks [7, 8]. This widespread integration has transformed decision-making processes across industries through diverse applications, including predictive analytics, automation of routine tasks, and optimization of resource management, enabling organizations to process vast amounts of data rapidly while reducing human error and enhancing strategic outcomes [9-11].

The operational benefits of AI integration are particularly evident in organizational efficiency gains, with key advantages encompassing improved operational efficiency, enhanced accuracy, and significant cost savings, especially notable in small and medium enterprises where AI tools substantially boost profitability [12, 13]. Explainable AI further enhances decision-making capabilities by providing transparent insights that are crucial for building trust and ensuring regulatory compliance [14]. Additionally, AI systems demonstrate exceptional capabilities in complex scenario forecasting and adaptive responses to dynamic environments, empowering organizations to maintain competitive advantages in rapidly changing markets [15, 16].

Research shows that generative AI tools can significantly improve workplace dynamics and individual productivity by reducing task completion time by up to 40% and improving output quality by 18%, particularly among less-skilled workers [17]. Furthermore, AI adoption correlates positively with increased job satisfaction, skill development, and innovative work behaviors [18, 19]. However, these productivity gains are accompanied by emerging challenges, including workplace anxiety and work withdrawal behaviors, particularly among individuals with avoidance-oriented personalities [20]. While AI integration generally supports enhanced technological self-efficacy and prosocial behaviors, organizations must carefully address adaptation challenges and employee well-being concerns [21-24].

Of particular concern is the relationship between generative AI usage and procrastination, which warrants critical investigation as AI tools become ubiquitous in academic and professional environments, fundamentally altering task management and motivational dynamics [25]. Theoretical frameworks such as the Conservation of Resources theory provide a compelling foundation for understanding this relationship, suggesting that human-AI interactions influence emotional states like boredom, which subsequently mediate procrastination behaviors [25]. Empirical evidence demonstrates that dependence on AI positively correlates with increased procrastination among university students [26] While overreliance on AI tools potentially diminishes personal initiative and self-regulation capabilities [27]. However, research also indicates that strategic AI integration, combining personalized reminders with peer motivation, can effectively reduce academic procrastination [28]. Furthermore, AI awareness impacts counterproductive workplace behaviors through psychological contract alterations and emotional exhaustion mechanisms [29] highlighting the dual nature of AI's influence on human behavior [30, 31].

The technical design of AI systems can inadvertently influence delay behaviors through poorly calibrated feedback timing and task processing mechanisms. Research demonstrates that feedback delivered too quickly may undermine user trust in AI understanding, while excessive delays cause frustration and disengagement, both of which promote procrastination behaviors [32]. The optimal feedback window of one to three seconds maintains engagement and supports timely task completion [32]. Additionally, inefficient scheduling in edge computing environments introduces unpredictable delays that negatively impact user experience [33, 34]. Time pressure dynamics further complicate human-AI collaboration, with performance improving when users have adequate decision time [35]. Trust and bias factors also influence delay behaviors, as users demonstrate increased acceptance of AI suggestions during difficult tasks regardless of accuracy [36]. These findings underscore the critical importance of designing AI systems with careful attention to temporal feedback mechanisms to minimize inadvertent encouragement of procrastination behaviors [37].

Despite extensive research on AI technical performance, critical aspects of AI-human interaction remain underexplored, particularly the systematic integration of ethical frameworks into AI systems [38]. Studies reveal significant gaps in understanding how responsibility and accountability are distributed between humans and AI, with individuals perceiving AI as less morally trustworthy and frequently shifting blame to developers [39]. The alignment of AI recommendations with human values and its impact on trust remains nascent [40] while collaborative ethical decision-making models lack comprehensive frameworks that ensure adequate human oversight and clear responsibility allocation [41]. Furthermore, the translation of ethical principles into transparent AI behavior continues to challenge researchers and practitioners [42-44].

Ethical decision-making emerges as a crucial mediating factor in AI-human interactions because it fundamentally determines how individuals navigate moral dilemmas introduced by AI tools, ensuring that technology aligns with societal values while avoiding harmful outcomes [45, 46]. Ethical considerations fundamentally influence AI use by guiding critical decisions about data handling, transparency, fairness, and accountability, while helping users recognize and effectively mitigate algorithmic biases [47, 48]. Moral reasoning significantly influences AI-assisted behaviors by determining whether individuals accept, question, or challenge system decisions, particularly as research shows that people perceive AI as more utilitarian and less empathetic than humans [49]. Individual moral foundations create diverse judgments about ethical AI use, with perceived ethicality varying substantially based on personal values and moral orientations [50, 51]. Consequently, robust ethical frameworks that effectively integrate moral principles into AI interactions are essential for responsible innovation and building sustainable trust in AI-driven systems [52].

Given the complex interplay between AI adoption, procrastination behaviors, and ethical considerations, this study aims to explore the mediating role of ethical decision-making in the relationship between generative AI usage and procrastination. By examining how ethical frameworks influence the impact of AI tools on delay behaviors, this research contributes to our understanding of responsible AI integration and provides insights for developing more effective human-AI collaboration models that promote both productivity and ethical behavior.

2. Literature Review

2.1. Generative AI and Human Behavior

The integration of generative AI tools into academic and professional environments has demonstrated significant impacts on human productivity and behavioral patterns. Empirical evidence consistently shows that AI tools can substantially enhance human performance, with controlled experiments revealing task completion time reductions of up to 40% and output quality improvements of 18%, particularly benefiting less-skilled workers [17]. These productivity gains are most pronounced when AI functions as a collaborative partner rather than a replacement, with human-AI collaboration proving especially effective in knowledge work settings [24, 53]. Digital productivity assistants further amplify these benefits through personalized work-based analytics [54].

However, the implementation of AI tools reveals a complex duality of outcomes. While successful integration can enhance efficiency and decision-making accuracy, particularly in specialized tasks such as predictive maintenance and healthcare diagnostics [55, 56], poorly implemented AI systems can increase stress levels and reduce job satisfaction [57]. AI assistance augments human cognitive processes by providing personalized support, boosting creativity, and increasing confidence in complex problem-solving scenarios [58, 59] yet raises substantial concerns regarding job displacement, reduced accountability, and diminished output diversity [21, 60].

The methodological approaches employed to measure generative AI usage and behavioral outcomes have evolved to encompass diverse research strategies. Researchers primarily utilize surveys and structural equation modeling to assess user intentions and behaviors, examining factors such as perceived usefulness, satisfaction, self-efficacy, and trust [61, 62]. Experimental designs compare AI-generated versus human responses in decision-making contexts [63] while studies integrate established behavioral theories like the Theory of Planned Behavior to understand AI adoption patterns [64-66]. Hybrid approaches combining partial least squares with artificial neural networks have emerged to predict consumer behaviors [66, 67] alongside vignette-based comparisons for evaluating AI recommendation appropriateness [68].

Understanding AI-human interaction requires multidisciplinary theoretical frameworks that integrate communication, psychology, and behavioral sciences. Human-Machine Communication (HMC) frameworks emphasize functional, relational, and metaphysical dimensions of AI interactions [69] while psychological theories focusing on trust, agency, and self-concept integration are central to AI adoption [70]. The Theory of Interactive Media Effects (TIME) framework helps understand the symbolic and enabling effects of AI-driven media on user perceptions [71]. Technology Acceptance Models have been adapted for generative AI contexts by incorporating perceived agency, explainability, and human-AI collaboration continuums [72]. Additionally, AI anthropomorphism affects self-congruence and self-AI integration processes [73] while comprehensive interaction frameworks consider human-AI fit and varying degrees of AI agency [74].

Critical ethical implications surrounding AI adoption include privacy concerns, data security risks, algorithmic bias, and transparency issues, with particular vulnerabilities identified in developing populations [56]. Employee attitudes toward AI adoption are significantly influenced by perceptions of AI capabilities and individual knowledge levels, ultimately affecting organizational implementation success [75]. These findings underscore that successful AI integration requires careful attention to user experience, implementation strategies, and the development of adaptive, trustworthy AI design for effective collaboration [76, 77].

2.2. Procrastination: Definitions, Causes, and Consequences

Contemporary research conceptualizes procrastination as the voluntary, irrational delay of intended actions despite expecting negative consequences, fundamentally representing a self-regulation failure that impedes goal achievement and well-being [78]. This definition distinguishes procrastination from purposeful delay by highlighting the interplay between task aversiveness, outcome utility, and temporal decision-making, where immediate discomfort outweighs perceived future benefits [79]. Self-regulation theory posits deficits in effort regulation and motivation as key drivers, with research demonstrating that effort regulation management accounts for 24% of the variance in procrastination behaviors [80].

Multidimensional models have evolved to incorporate psychological, social, academic, and environmental factors, which are particularly relevant in student populations [81]. Measurement approaches utilize validated instruments, including the General Procrastination Scale (GPS), Irrational Procrastination Scale (IPS), and Pure Procrastination Scale (PPS), all focusing on irrational delay patterns [82-84]. Recent developments distinguish between onset and sustained procrastination and incorporate workplace-specific measures such as the Procrastination at Work Scale (PAWS) for organizational contexts [85, 86].

The antecedents of procrastination reveal a complex interplay of individual, technological, and environmental factors. Individual traits serve as primary predictors, with low conscientiousness, poor self-regulation, and low self-efficacy consistently emerging as core variables across age groups and contexts [87]. Technological factors significantly influence procrastination behaviors, as mobile phone addiction and excessive internet use positively correlate with procrastination among students [88]. Situational variables, including poor sleep quality and social sleep lag, contribute to self-regulatory failure [89] while environmental factors such as parenting style show weaker effects compared to personality traits [90]. Notably, social interdependence through group work can mitigate procrastination tendencies [91] and academic procrastination is associated with declining metacognitive self-regulation over time [92].

The consequences of procrastination in academic and professional contexts demonstrate significant detrimental effects on performance, well-being, and achievement outcomes. Research consistently shows that procrastination is associated with lower academic satisfaction, diminished affective well-being, and increased symptoms of anxiety and depression [93, 94]. Chronic procrastinators experience higher stress levels, engage in fewer healthy behaviors, and face greater health risks over time, with stress serving as a key mediator between procrastination and negative health outcomes [95]. Long-term implications reveal that habitual procrastination represents a marker of self-regulation failure, creating maladaptive patterns that further impair achievement and well-being [86, 96]. Despite intervention efforts, particularly cognitive-behavioral approaches, show promise in reducing procrastination behaviors [27], the problem remains widespread with lasting consequences for performance, health, and life satisfaction.

2.3. Ethical Decision-Making in Technology Contexts

Ethical decision-making is defined as the systematic process through which individuals identify, evaluate, and select alternatives consistent with moral principles and values [97]. Research operationalizes this construct through structured models encompassing core procedural steps, including dilemma evaluation, information gathering, risk consideration, and action selection [98]. Theoretical frameworks span from rationalist-based approaches emphasizing logical reasoning to non-rationalist models highlighting intuition and emotion [99]. Contemporary integrative models, such as Schwartz's [97] Integrated Ethical Decision-Making framework, bridge these perspectives by incorporating both cognitive and affective processes alongside individual and situational factors [97]. Dual-process models increasingly demonstrate explanatory power in complex situations [100] while specialized frameworks like Moral Utility Theory conceptualize ethical choices as subjective expected utility calculations [101]. Domain-specific models integrate cultural, organizational, and legal standards, particularly in business and AI contexts [45, 102].

Ethics serve as a fundamental determinant in technology adoption and usage by establishing frameworks that guide responsible implementation and user acceptance [103, 104]. Previous research demonstrates that ethical considerations directly influence user attitudes, trust, and willingness to adopt emerging technologies, particularly in AI applications [105, 106]. The field has evolved from establishing high-level ethical principles to developing practical frameworks addressing real-world challenges through inclusive design and stakeholder engagement [107]. Key factors influencing ethical decision-making in digital environments include organizational culture, regulatory standards, perceived risks and benefits, and the integration of accountability, fairness, and privacy considerations into technology development processes [108-110].

Ethical reasoning serves as a fundamental framework for responsible AI tool usage, guiding users through complex dilemmas involving privacy, fairness, transparency, and accountability, particularly in high-stakes academic and professional environments [111]. Generative AI presents distinctive ethical challenges, including bias propagation, misinformation dissemination, privacy violations, and risks of academic dishonesty such as plagiarism and deceptive content creation [112, 113]. These concerns are amplified by detection difficulties and potential for facilitating cyberattacks while exacerbating social inequalities [114]. Individual differences in ethical reasoning, shaped by personal values, cultural norms, and professional standards, significantly influence AI technology adoption patterns, with ethically aware users demonstrating greater caution and selectivity [115, 116]. However, current AI ethics frameworks often lack practical guidance for navigating organizational power dynamics and translating high-level principles into actionable strategies [117, 118].

3. Method

3.1. Participants

The study employed a two-phase data collection approach involving participants from multiple institutions across Egypt and Kuwait. The total sample comprised 1,288 participants across two distinct phases.

3.2. Main Sample

The primary sample consisted of 727 participants recruited from two institutions: Al-Azhar University in Egypt and the College of Basic Education, Public Authority for Applied Education and Training in Kuwait. The sample showed a predominant female representation with 609 female participants (83.8%) and 118 male participants (16.2%). Age distribution revealed four distinct groups: 101 participants (13.9%) aged 18-22 years, 262 participants (36.0%) aged 23-27 years, 94 participants (12.9%) aged 28-30 years, and 270 participants (37.1%) aged 31-35 years. Educational attainment varied across four levels: 50 participants (6.9%) held doctoral degrees, 87 participants (12.0%) possessed master's degrees, 374 participants (51.4%) had graduate diploma qualifications from Al-Azhar University, Egypt, and 216 participants (29.7%) were undergraduate students from the College of Basic Education, Public Authority for Applied Education and Training, Kuwait. Regarding residential background, 250 participants (34.4%) resided in urban areas while 477 participants (65.6%) came from rural settings. All participants in the main sample (100%) confirmed their utilization of generative AI tools.

3.3. Validation Sample

A secondary validation sample of 561 participants was selected from students enrolled at three specific facilities: the Faculty of Education for Boys in Dakahlia and the Faculty of Education for Girls in Cairo (both at Al-Azhar University, Egypt), and the College of Basic Education, Public Authority for Applied Education and Training, Kuwait. Data collection was conducted through an electronic survey administered via Google Forms. This validation sample consisted of 91 males (16.2%) and 470 females (83.8%). Participants' ages were distributed across four categories: 18-22 years (82 participants, 14.6%), 23-27 years (208 participants, 37.1%), 28-30 years (72 participants, 12.8%), and 31-35 years (199 participants, 35.5%). Educational levels included 31 participants (5.5%) with doctoral degrees, 52 participants (9.3%) with master's degrees, 410 participants (73.1%) with graduate diploma degrees from Al-Azhar University, Egypt, and 68 participants (12.1%) were undergraduate students from the College of Basic Education, Public Authority for Applied Education and Training, Kuwait.

3.4. Instruments

3.4.1. ChatGPT Usage Scale

The study employed the ChatGPT Usage Scale developed by Nemt-allah et al. [119], which consists of 15 items distributed across three dimensions: Academic Writing Aid (7 items), Academic Task Support (4 items), and Reliance and Trust (4 items). Each item is rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The scale demonstrated excellent psychometric properties in the current study. For the Academic Writing Aid dimension, reliability coefficients were robust with McDonald's $\omega = 0.934$, Cronbach's $\alpha = 0.934$, Guttman's $\lambda 2 = 0.934$, Guttman's $\lambda 6 = 0.928$, and Greatest Lower Bound = 0.948. The Academic Task Support dimension showed similarly strong reliability with McDonald's $\omega = 0.922$, Cronbach's $\alpha = 0.922$, Guttman's $\lambda 2 = 0.922$, Guttman's $\lambda 6 = 0.900$, and Greatest Lower Bound = 0.930. The Reliance and Trust dimension exhibited adequate reliability with McDonald's $\omega = 0.843$, Cronbach's $\alpha = 0.835$, Guttman's $\lambda 2 = 0.841$, Guttman's $\lambda 6 = 0.821$, and Greatest Lower Bound = 0.857. The overall scale demonstrated exceptional reliability with McDonald's $\omega = 0.964$, Cronbach's $\alpha = 0.964$, Guttman's $\lambda 2 = 0.964$, Guttman's $\lambda 6 = 0.967$, and Greatest Lower Bound = 0.977. Confirmatory factor analysis revealed acceptable model fit indices with CMIN/DF = 4.968, GFI = 0.903, AGFI = 0.866, NFI = 0.943, RFI = 0.931, IFI = 0.954, TLI = 0.944, CFI = 0.954, and RMSEA = 0.084.

3.4.2. Ethical Student Scale

The Ethical Student Scale, developed by Rua, et al. [119], was utilized to measure ethical decision-making behaviors. The scale comprises 9 items distributed across three dimensions, with each dimension containing 3 items: Rules and Policies, Personal Morality, and Pressure to Perform. Items are rated on a 5-point Likert scale. The Rules and Policies dimension demonstrated good reliability with McDonald's $\omega = 0.829$, Cronbach's $\alpha = 0.827$, Guttman's $\lambda 2 = 0.828$, Guttman's $\lambda 6 = 0.765$, and Greatest Lower Bound = 0.829. The Personal Morality dimension showed excellent reliability with McDonald's $\omega = 0.923$, Cronbach's $\alpha = 0.922$, Guttman's $\lambda 2 = 0.922$, Guttman's $\lambda 6 = 0.892$, and Greatest Lower Bound = 0.923. The Pressure to Perform dimension exhibited adequate reliability with McDonald's $\omega = 0.789$, Cronbach's $\alpha = 0.759$, Guttman's $\lambda 2 = 0.771$, Guttman's $\lambda 6 = 0.747$, and Greatest Lower Bound = 0.789. The overall scale demonstrated good reliability with McDonald's $\omega = 0.840$, Cronbach's $\alpha = 0.858$, Guttman's $\lambda 2 = 0.866$, Guttman's $\lambda 6 = 0.906$, and Greatest Lower Bound = 0.927. Confirmatory factor analysis supported the factor structure with excellent model fit indices: CMIN/DF = 1.981, GFI = 0.982, AGFI = 0.967, NFI = 0.984, RFI = 0.977, IFI = 0.992, TLI = 0.988, CFI = 0.992, and RMSEA = 0.042.

3.4.3. Academic Procrastination Scale - Short Form

The Academic Procrastination Scale - Short Form, validated by Yockey [121], was employed to measure students' tendency to procrastinate on academic tasks. The scale consists of five items rated on a five-point Likert scale. The scale demonstrated good reliability in the current study, with McDonald's ω = 0.855, Cronbach's α = 0.852, Guttman's λ2 = 0.854, Guttman's λ6 = 0.827, and the Greatest Lower Bound = 0.873. Confirmatory factor analysis revealed an acceptable model fit, with CMIN/DF = 3.335, GFI = 0.988, AGFI = 0.965, NFI = 0.985, RFI = 0.971, IFI = 0.990, TLI = 0.979, CFI = 0.990, and RMSEA = 0.065.

3.5. Data Analysis

Data analysis was conducted using IBM SPSS software. Descriptive statistics were calculated for all variables, revealing the following distributions: ChatGPT usage (M = 53.86, SD = 7.44, Range = 39.00), Ethical Decision-Making (M = 34.74, SD = 5.80, Range = 36.00), and Procrastination (M = 10.06, SD = 2.65, Range = 10.00). Mediation analysis was performed using Model 4 of the PROCESS macro for IBM SPSS, developed by Hayes, to explore the mediating role of ethical decision-making in the relationship between generative AI usage and procrastination. Bootstrap confidence intervals were calculated using 5,000 bootstrap samples with a 95% confidence level to test the significance of indirect effects.

4. Results

4.1. Descriptive Statistics

The analysis included 727 participants from Al-Azhar University, Egypt, and the College of Basic Education, Public Authority for Applied Education and Training, Kuwait. Descriptive statistics revealed the following distributions: ChatGPT usage (M = 53.86, SD = 7.44), Ethical Decision-Making (M = 34.74, SD = 5.80), and Academic Procrastination (M = 10.06, SD = 2.65).

4.2. Mediation Analysis

To address the primary research objective of exploring the mediating role of ethical decision-making in the relationship between generative AI usage and procrastination, a mediation analysis was conducted using Model 4 of the PROCESS macro for IBM SPSS [38]. Bootstrap confidence intervals were calculated using 5,000 bootstrap samples with a 95% confidence level.

4.3. Direct Effects

The analysis revealed several significant direct relationships among the study variables (see Table 1) Generative AI usage significantly and positively predicted ethical decision-making (β = .1181, SE = .0287, t = 3.202, p < .001, 95% CI [.0356, .1484]), indicating that higher levels of AI usage were associated with enhanced ethical decision-making behaviors.

Generative AI usage also demonstrated a significant negative direct effect on academic procrastination (β = -.2083, SE = .0128, t = -5.791, p < .001, 95% CI [-.0994, -.0491]), suggesting that increased AI usage was associated with reduced procrastination behaviors.

Furthermore, ethical decision-making significantly and negatively predicted academic procrastination (β = -.1590, SE = .0165, t = -4.420, p < .001, 95% CI [-.1051, -.0404]), indicating that stronger ethical decision-making was associated with lower levels of procrastination.

4.4. Total and Indirect Effects

The total effect of generative AI usage on academic procrastination was significant and negative (β = -.2271, SE = .0129, t = -6.278, p < .001, 95% CI [-.1063, -.0556]), accounting for 5.16% of the variance in procrastination scores (R^2 = .0516).

The indirect effect of generative AI usage on procrastination through ethical decision-making was statistically significant (β = -.0067, Bootstrap SE = .0026, 95% Bootstrap CI [-.0126, -.0022]). This indirect effect accounted for approximately 8.27% of the total effect, indicating partial mediation.

The direct effect of generative AI usage on procrastination, after controlling for the mediator, remained significant (β = -.2083, SE = .0128, t = -5.791, p < .001, 95% CI [-.0994, -.0491]), accounting for 91.73% of the total effect.

Table 1.
Mediation Analysis Results: Direct and Indirect Effects.

Pathway	β	SE	t	95% CI	R^2
Gen.AI → Ethical Decision-Making	0.118^{***}	0.028	3.202	[0.035, 0.148]	0.014
Gen.AI → Procrastination	-0.208^{***}	0.012	-5.791	[-.099, -0.049]	0.077
Ethical Decision-Making → Procrastination	-0.159^{***}	0.016	-4.420	[-0.105, -0.040]	0.077
Total Effect					
Gen.AI → Procrastination	-0.227^{***}	0.012	-6.278	[-0.106, -0.055]	0.052
Indirect Effect					
Gen.AI → Ethical Decision-Making → Procrastination	-0.0067^{*}	0.002	—	[-0.012, -.002]	—

Note: N = 727, *** p < .001, Bootstrap confidence intervals based on 5,000 bootstrap samples. *Indicates significance based on bootstrap confidence interval not containing zero.

4.5. Model Fit and Variance Explained

The mediation model demonstrated adequate explanatory power. The model predicting ethical decision-making from generative AI usage accounted for 1.39% of the variance ($R^2 = .014$, $F(1,725) = 10.253$, $p = .001$). The full model predicting procrastination from both generative AI usage and ethical decision-making explained 7.65% of the variance ($R^2 = .077$, $F(2,724) = 29.977$, $p < .001$). The mediation model is illustrated in Figure 1, which displays the standardized path coefficients for all relationships in the model.

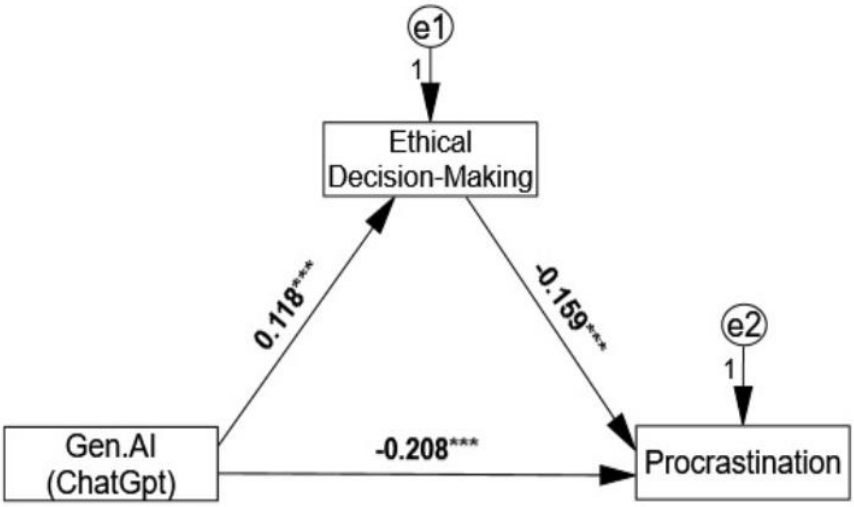

Figure 1.
Conceptual Mediation Model with Standardized Path Coefficients.
Note: *** $p < .001$.

The mediation analysis supported the hypothesized model, revealing that ethical decision-making partially mediates the relationship between generative AI usage and academic procrastination. While the indirect effect was relatively small (8.27% of the total effect), it was statistically significant, indicating that part of the relationship between AI usage and reduced procrastination operates through enhanced ethical decision-making processes. The predominant direct effect (91.73%) suggests that generative AI usage influences procrastination through multiple pathways beyond ethical considerations.

5. Discussion

The present study investigated the mediating role of ethical decision-making in the relationship between generative AI usage and academic procrastination among university students from Egypt and Kuwait. The findings reveal a complex interplay between these variables, with ethical decision-making serving as a significant, albeit partial, mediator in this relationship.

The research reveals a significant negative correlation between generative AI usage and academic procrastination, challenging common assumptions about technology's potential to encourage delay behaviors. Students who use AI tools more frequently show reduced procrastination tendencies, aligning with recent empirical evidence indicating productivity gains from AI integration, with task completion times potentially reduced by up to 40% [17]. Research further demonstrates that AI adoption correlates positively with increased job satisfaction, skill development, and innovative work behaviors [18]. The negative correlation may indicate AI's ability to reduce task aversiveness, a key factor in procrastination, by offering immediate assistance, simplifying complex tasks, and boosting student confidence.

The positive relationship between generative AI usage and ethical decision-making ($\beta = .118$, $p < .001$) represents another significant contribution to the literature. This finding suggests that increased engagement with AI tools is associated with enhanced ethical reasoning capabilities, potentially reflecting students' growing awareness of moral complexities surrounding AI implementation. Research demonstrates that ethical considerations fundamentally influence AI use by guiding critical decisions about data handling, transparency, fairness, and accountability [47]. Additionally, studies reveal that moral reasoning significantly influences AI-assisted behaviors by determining whether individuals accept, question, or challenge system decisions [49]. Ethical decision-making is crucial in AI-human interactions because it influences how individuals navigate moral dilemmas introduced by AI tools, ensuring that technology aligns with societal values and avoids harmful outcomes [45]. Regular interaction with AI systems exposes users to ethical dilemmas related to academic integrity, authenticity, and responsible technology use. Modern AI tools' transparency encourages systematic evaluation of information sources and decision-making processes. The collaborative nature of human-AI interaction promotes metacognitive awareness about the boundaries between human judgment and algorithmic assistance, leading to more nuanced ethical decision-making frameworks.

The mediating role of ethical decision-making, while statistically significant, accounts for a relatively modest portion of the total effect (8.27%). This partial mediation indicates that ethical reasoning serves as one pathway through which AI usage influences procrastination, but multiple other mechanisms are likely at work. The substantial direct effect (91.73%) suggests that generative AI tools influence procrastination through various channels beyond moral considerations, including cognitive load reduction, enhanced task engagement, improved self-efficacy, and more efficient workflow management. This finding underscores the multifaceted nature of human-AI interaction and suggests that ethical frameworks, while important, represent just one component of a broader ecosystem of factors influencing behavioral outcomes.

The study suggests that the negative correlation between AI usage and procrastination may be due to AI tools' enhanced regulatory capacity, indicating that generative AI systems can assist in self-regulatory processes. The technology may compensate for individual deficits in effort regulation and motivation, key drivers of procrastination identified in previous research [80]. Research consistently demonstrates that procrastination is associated with self-regulation failure, creating maladaptive patterns that impair achievement and well-being [96]. By reducing the cognitive burden associated with task initiation and execution, AI tools may enable students to overcome the self-regulation failures that characterize procrastination behavior.

AI usage positively impacts ethical decision-making, aligning with moral development theories. Exposure to complex ethical scenarios enhances moral reasoning, while integrating AI tools into academic work presents unique ethical challenges. Research shows that individual moral foundations create diverse judgments about ethical AI use, with perceived ethicality varying substantially based on personal values and moral orientations [50]. Contemporary integrative models, such as Schwartz [97]. Integrated Ethical Decision-Making Framework, bridging cognitive and affective processes alongside individual and situational factors [97]. Studies demonstrate that ethical reasoning serves as a fundamental framework for responsible AI tool usage, guiding users through complex dilemmas involving privacy, fairness, transparency, and accountability [111]. Students must develop sophisticated ethical frameworks to navigate challenges such as AI assistance, academic integrity, and efficiency, thereby strengthening ethical decision-making capabilities beyond AI-specific contexts.

From a Technology Acceptance perspective, these findings suggest that ethical considerations play a more nuanced role in technology adoption than previously understood. Rather than serving merely as barriers to adoption, ethical frameworks appear to facilitate more thoughtful and sustainable technology integration. Students who develop stronger ethical decision-making capabilities may be better positioned to harness AI's benefits while avoiding potential pitfalls, leading to more effective and responsible use patterns that ultimately reduce procrastination.

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The practical implications of these findings are significant for educational institutions, instructors, and students navigating the integration of AI tools in academic contexts. For educational institutions, the results suggest that policies restricting AI usage may be counterproductive if the goal is to promote student productivity and reduce procrastination. Instead, institutions might focus on developing comprehensive AI literacy programs that emphasize both technical competencies and ethical reasoning skills. Such programs could help students maximize the productivity benefits of AI tools while maintaining academic integrity and developing critical thinking capabilities.

For instructors, these findings highlight the importance of explicit discussions about ethical AI use rather than blanket prohibitions. Classroom conversations about responsible AI integration, academic integrity boundaries, and the development of human-AI collaboration skills may be more effective than restrictive policies. Instructors might consider incorporating structured ethical reflection exercises that help students develop frameworks for evaluating AI assistance in different academic contexts. Additionally, assignment design could explicitly accommodate AI usage while maintaining learning objectives, potentially reducing student anxiety and procrastination while promoting ethical reflection.

For students, the results suggest that strategic AI integration, coupled with ethical reflection, may enhance rather than undermine academic performance. Students can be encouraged to develop personal ethical frameworks for AI usage that consider factors such as learning objectives, academic integrity requirements, and skill development goals. The findings also suggest that students who engage thoughtfully with the ethical dimensions of AI usage may experience additional benefits in terms of reduced procrastination and enhanced decision-making capabilities. Moreover, the study's practical implications are robust due to its cross-cultural nature, indicating that the findings may apply to various Arab cultural contexts.

The study has several limitations. Its cross-sectional design and focus on a single institution with a predominantly female sample limit the generalizability of the findings. Future research should explore procrastination relationships across diverse educational contexts, cultural backgrounds, and demographic groups. Additionally, future studies should incorporate behavioral measures, objective assessments of AI usage patterns, and experimental manipulations of ethical frameworks. Different types of AI usage and ethical dilemmas should be examined, and various ethical frameworks or moral orientations could offer more nuanced insights.

6. Conclusion

This study provides evidence that generative AI usage is associated with reduced academic procrastination and that this relationship is partially mediated by ethical decision-making processes. While the mediating effect is modest, it suggests that moral reasoning serves as one pathway through which AI tools influence student behavior. These findings challenge common assumptions about AI's potential negative effects on self-regulation and suggest that thoughtful integration of AI tools, accompanied by ethical reflection, may enhance rather than undermine academic productivity. The results underscore the importance of developing comprehensive approaches to AI integration in educational contexts that emphasize both technical capabilities and ethical reasoning skills. As AI tools become increasingly prevalent in academic and professional environments, understanding the complex relationships between technology use, moral reasoning, and behavioral outcomes will be crucial for promoting responsible innovation and maximizing the benefits of human-AI collaboration.

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