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Ethical decision making and astute use of artificial intelligence

Mohamad Noorman Masrek[1]*, Heriyanto[2], Abid Hussain[3]
[1]Faculty of Information Science, Universiti Teknologi MARA Selangor Branch, Shah Alam, Malaysia; mnoorman@uitm.edu.my (M.N.M.).
[2]Fakultas Ilmu Budaya, Universitas Diponegoro, Semarang, Indonesia; heriyanto@live.undip.ac.id (H.).
[3]Institute of Strategic Studies, Islamabad, Pakistan; abidhussain@issi.org.pk (A.H.).

Abstract: This study examines the relationship between ethical decision-making and the astute use of artificial intelligence (AI) among university students in Malaysia. As AI becomes increasingly integrated into learning and future professional activities, understanding how ethical considerations shape AI usage is essential. Guided by Rest's Four-Component Model of ethical decision-making and the Digital Intelligence framework, this research investigates whether students' ethical reasoning influences their responsible engagement with AI tools. A survey was administered to university students using a structured questionnaire, and the data were analyzed through descriptive statistics and partial least squares structural equation modeling. The findings demonstrate a positive relationship between ethical decision-making and students' astute use of AI, indicating that ethical awareness contributes meaningfully to how students interact with AI technologies. The study concludes that ethical competence plays a critical role in shaping students' digital practices. These results offer important implications for educators, policymakers, and university administrators seeking to develop ethical guidelines, training modules, and institutional policies that promote responsible AI use in higher education and prepare students for ethical decision-making in AI-driven environments.

Keywords: *Artificial intelligence, Astute use, Ethical decision making.*

1. Introduction

Artificial Intelligence (AI) has existed for decades, but it has only recently blossomed within society to a significant extent. Today, AI is ubiquitous, from personal assistants like smartphones to complex algorithms powering autonomous vehicles [1, 2]. AI has permeated various aspects of human life, including the development of smart cars (self-driving) equipped with sophisticated algorithms. These technologies have had a distinctive impact across multiple sectors, with academia being a notable example. However, the introduction of AI into academia remains controversial [3]. While AI has the potential to greatly enhance scientific research, teaching, and learning, it also raises ethical concerns that require careful consideration. The rapid integration of AI into these fields necessitates scrutiny of its implications for academic integrity and the future of education [4]. As AI becomes increasingly common, its impact is being felt by all, whether we recognize it or not. Any company or individual choosing not to adopt AI risks missing out on its many benefits. AI-powered tools are driving innovation and efficiency across industries, and those who do not embrace AI may fall behind their competitors [5]. With growing interest in AI technology driving advancements in various fields, opting out of AI adoption presents a competitive disadvantage [6].

The widespread adoption of AI raises important questions about the future of humanity: Are we exercising astute judgment in our use of AI? Previous studies indicate that AI usage among university students has both positive and negative effects. For instance, one found that students often rely on ChatGPT to generate research content without fully understanding the ethical implications [7].

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* Correspondence: mnoorman@uitm.edu.my

Similarly, another study found that students are more likely to engage in unauthorized copying of AI-generated material compared to content created by humans [8]. Furthermore, this research revealed that students perceive plagiarism of AI-generated content as less unethical and more permissible [9]. These findings highlight the ethical challenges posed by integrating AI technology into academic settings. According to Elmessiry et al. [10], the unethical use of AI in education can lead to the dehumanization of the learning experience, reducing education to a mere transactional process. This underscores the importance of considering the ethical implications of AI adoption in educational contexts.

Rest proposed a model for ethical decision-making with four dimensions: moral sensitivity, moral judgment, moral motivation, and moral character [11]. However, past research has often overlooked all four dimensions, revealing a gap in the literature regarding comprehensive moral assessment [12]. Moreover, previous studies on the assessment of moral studies have primarily focused on students in health-related programs and engineering [12-15]. Limited research specifically examines the link between ethical decision-making and the astute use of technology, particularly AI. This gap highlights the need for further research to explore the complex interplay between ethical decision-making and responsible AI usage in academic settings. Accordingly, the following objectives are established for this research: (i) to examine how students perceive their ethical decision-making processes, (ii) to explore how students perceive their astute use of AI, and (iii) to develop a model that examines the relationship between ethical decision-making and the astute use of AI.

2. Theoretical Framework and Hypothesis Development

2.1. Ethical Decision Making

Ethical decision-making is influenced by personal beliefs, societal norms, organizational culture, and situational factors [16]. Individuals must consider the potential consequences of their actions and aim to make choices that promote fairness, justice, and integrity. Rest's Four-Component Model offers a framework for understanding the cognitive processes involved in ethical decision-making [11]. This model includes four components: moral sensitivity, moral judgment, moral motivation, and moral character. Moral sensitivity is the ability to recognize moral issues and empathize with others' perspectives. Moral judgment involves reasoning and deliberation to determine the right course of action based on ethical principles. Moral motivation refers to the individual's willingness to prioritize ethical values over personal interests or external pressures. Lastly, moral character reflects the consistency and integrity of an individual's ethical behavior over time.

The connection between ethical decision-making and ethical behavior is essential for fostering a culture of integrity and responsibility [17, 18]. While ethical decision-making provides a framework for evaluating moral dilemmas and making informed choices, ethical behavior involves translating those decisions into action. Individuals who consistently exhibit ethical behavior uphold standards, contributing to trust within organizations and society. By aligning ethical decision-making with ethical behavior, both individuals and organizations can create environments that prioritize integrity, respect, and social responsibility [19].

2.2. Digital Intelligence

Digital intelligence encompasses a broad spectrum of competencies and skills necessary for effectively navigating the digital landscape. In today's interconnected world, individuals need not only technical proficiency but also critical thinking, ethical decision-making, and a keen awareness of digital rights and responsibilities. The Digital Quotient (DQ) framework, as outlined by the DQ Institute, identifies several components of digital intelligence, including digital rights, digital literacy, digital communication, digital emotional intelligence, digital security, digital safety, digital use, and digital identity [20]. Together, these components equip individuals to engage with digital technologies responsibly, ethically, and effectively.

In modern universities, digital intelligence is essential for students to succeed academically, foster personal growth, and prepare for professional advancement. In educational settings, students frequently use electronic communications, digital tools, and online platforms for interaction [21]. Moreover, understanding digital security and safety is crucial to protect personal information, guard against cyber threats, and maintain online privacy [22]. Digital emotional intelligence, understanding and managing one's own emotions, as well as the emotions of others in digital environments, is key to managing online interactions, navigating social media, and maintaining mental well-being [23]. Developing digital intelligence enables university students to learn, grow, and succeed while mitigating risks and challenges associated with digital technology use [24].

In today's digital age, digital intelligence is a critical workplace skill. Employers seek candidates who can effectively use digital tools, communicate, and collaborate in a digital environment [25]. Individuals well-versed in digital rights, ethical considerations, and responsible digital use are better equipped to handle ethical dilemmas and make informed career decisions [26]. Digital intelligence includes skills like critical thinking, problem-solving, creativity, and communication. Students developing digital intelligence during university improve their competitiveness in the job market, adapt to changing digital technologies, and contribute positively to workplaces and communities [27].

2.3. Astute Use of Technology

Astute use of technology involves careful and discerning engagement with digital tools and platforms to maximize benefits while minimizing potential drawbacks or harms. It entails using technology thoughtfully, responsibly, and strategically, considering ethical, social, and personal implications [28]. Astute users of technology adopt a realistic approach to digital utilization, prioritizing digital wellness, actively managing their digital well-being, and using technology to support others through digital interactions [29]. The DQ Institute identifies three key dimensions of astute technology use: balanced use, healthy use, and civic use.

Balance use entails managing one's digital consumption, recognizing that technology can be a powerful tool for both positive and negative outcomes. Balance promotes overall well-being by preventing excessive dependence or addiction to technology. Healthy use involves adopting practices that prioritize physical and mental wellness in digital environments, such as setting screen time limits, applying digital detox techniques, and encouraging meaningful and healthy online friendships [30]. Civic use focuses on leveraging technology to address society's information needs, advocating for intellectual property and digital rights, promoting digital inclusion, and highlighting social issues through digital awareness and engagement [31].

In the context of AI, particularly generative AI like ChatGPT, balanced use, healthy use, and civic use become especially relevant [32]. Balance use involves managing the time and frequency of interactions with AI-powered tools to maintain a healthy equilibrium between human-led and AI-driven activities [33]. Healthy use emphasizes prioritizing mental and emotional well-being when engaging with generative AI, being mindful of its potential to influence emotions, perceptions, and behaviors [34]. Civic use of generative AI includes utilizing AI technologies to address societal challenges, promote digital literacy, and foster ethical AI practices that uphold human values and rights [35].

2.4. Research Model

Rest's Model outlines four dimensions, moral sensitivity, moral judgment, moral motivation, and moral character, that guide ethical decision-making, which has significant implications for university students' attitudes and behaviors regarding the astute use of AI. University students are exposed to a variety of AI technologies in their academic studies, research projects, and daily lives. Moral sensitivity enables students to identify ethical issues arising from AI use, such as concerns about privacy, bias, and accountability [36]. Moral judgment allows students to assess the ethical implications of AI applications in their academic work and decision-making processes, ensuring they consider the potential consequences and whether AI use aligns with the ethical principles and values upheld by their academic institutions. Moral motivation drives students' commitment to ethical AI use, encouraging them to prioritize ethical considerations over personal interests or external pressures. This fosters a sense of responsibility and conscientious AI use that aligns with academic integrity standards [37].

Moreover, the dimensions of astute AI use, balanced use, healthy use, and civic use are closely intertwined with ethical decision-making among university students. Balance use involves managing digital consumption of AI technologies to maintain academic productivity while avoiding distractions and burnout. This balance entails effectively utilizing AI tools for academic tasks while engaging in offline activities that promote well-being and personal growth [38]. Healthy use emphasizes practices that prioritize students' mental and physical wellness when interacting with AI, such as setting boundaries on screen time, taking breaks, and seeking support when needed. Civic use encourages students to leverage AI technologies to positively contribute to their academic community and society at large, advocating for digital rights, promoting ethical AI practices, and addressing societal challenges through responsible digital citizenship.

As students demonstrate higher levels of ethical decision-making, characterized by moral sensitivity, judgment, motivation, and character [39], they are more likely to engage in astute behaviors when interacting with AI technologies. Moral sensitivity enables students to recognize ethical dilemmas inherent in AI use and discern the potential consequences of their actions. Students with heightened moral sensitivity are more attuned to ethical considerations surrounding AI technologies, such as issues related to privacy, bias, and social impact [40]. This awareness prompts them to approach AI use with greater caution and mindfulness, contributing to a more responsible and astute utilization of AI. Moral judgment empowers students to evaluate the ethical implications of AI applications and make informed decisions that align with ethical principles and values. When faced with ethical dilemmas in their interactions with AI, students with well-developed moral judgment are better equipped to assess potential risks and benefits, weigh competing interests, and determine the most ethically sound course of action. This ability to make ethically informed decisions fosters a more thoughtful and responsible approach to AI use. Based on this understanding, the research model of the study was developed, as shown in Figure 1, leading to the hypothesis: *H1 - There is a positive and significant relationship between ethical decision-making and astute use of AI.*

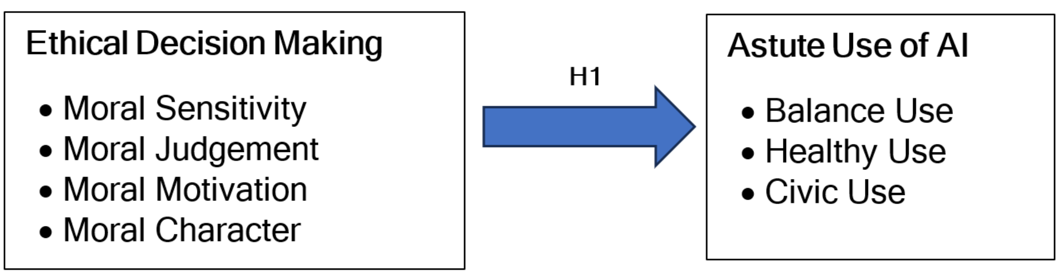

Figure 1.
Theoretical Framework.

3. Research Methodology

This study adopts a positivist research paradigm, characterized by its objective and empirical approach to inquiry. In this approach, researchers aim to understand the world through observation and measurement rather than subjective interpretation. The emphasis is on the quantification and measurement of phenomena, enabling more precise and generalizable claims about the relationship between ethical decision-making and the astute use of AI among university students. The survey method facilitates data collection from a large and diverse sample, allowing for a systematic examination of variables and their interrelationships.

3.1. Questionnaire

The questionnaire used in this study was carefully developed by referencing previous research [41, 42] to ensure the incorporation of validated measures and items that have demonstrated reliability and validity in assessing the constructs of interest. Given the inherent challenges of obtaining objective measures for abstract constructs such as ethical decision-making and AI usage behaviors, a perceptual measure approach was adopted, in line with common practice in Information Systems (IS) studies. Each construct in the questionnaire comprised five items, utilizing a Likert scale ranging from "strongly agree" to "strongly disagree," enabling participants to express their perceptions and attitudes with nuance. Rigorous validation procedures, as suggested by Masrek and Heriyanto [43], were undertaken, including pre-testing by two subject matter experts and pilot testing with 30 students. These efforts resulted in a Cronbach's alpha coefficient exceeding 0.7, indicating high internal reliability and consistency of the questionnaire items.

3.2. Population and Sampling

The population for this study comprised students enrolled in universities across Malaysia, with a convenience sampling adopted due to the unavailability of a sampling frame. Despite the absence of a defined sampling frame, convenient sampling was considered appropriate for this study, as the primary focus was on theory generalization rather than population generalization [44]. The targeted sample was identified through the researcher's networks, leveraging connections within university settings such as lectures and academic departments to recruit potential participants. Data collection took place over one month, providing ample time to gather responses from the identified sample.

3.3. Data Analysis

The data analysis in this study was designed to meet the specific needs of the research, utilizing a combination of descriptive analysis and partial least squares structural equation modeling (PLS-SEM) to address the study's objectives. Research objectives one (RO1) and two (RO2) focused on exploring and describing the prevalence and patterns of ethical decision-making and astute use of AI (AI) among university students. To achieve these objectives, descriptive statistical techniques were employed to summarize and interpret the survey responses, providing insights into the data's distribution, central tendency, and variability. Conversely, research objective three (RO3) aimed to examine the complex relationships between ethical decision-making and astute AI use, requiring a more advanced analytical approach. Given the exploratory nature of the study and the absence of a predefined theoretical model, such as the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT), PLS-SEM was deemed appropriate for analyzing the data. PLS-SEM facilitates the examination of complex causal relationships and hypothesis testing in situations where the theoretical framework is emergent or not based on established theories, making it well-suited for the objectives of this study [45].

4. Results

4.1. Common Method Bias

To assess the presence of common method bias, the Harman single-factor test was conducted [44]. This statistical technique determines whether a single underlying factor accounts for the majority of the variance in the data, which would indicate potential method bias. In this study, the Harman single-factor test revealed that the total variance extracted was 32%, which is well below the commonly accepted cut-off value of 50%. This result suggests that a single factor does not account for the majority of the variance, indicating that common method bias is not a significant concern in this study.

4.2. Demographic Profiles

Table 1 presents the demographic profiles of the respondents, indicating a slightly higher representation of females, who comprise 57.3% of the total sample, compared to males, who make up

42.7% of the participants. In terms of age distribution, the majority of respondents fall within the 18 to 25-year-old range, with 34.4% in the 18-21 age group and 34.9% in the 22-25 age bracket. A smaller proportion, 17.1%, is aged between 26 and 29 years old. Regarding educational attainment, the sample includes participants with varied levels of education. The largest proportion holds a bachelor's degree, accounting for 52.4% of respondents, followed by individuals with a diploma, comprising 23% of the sample. A notable 23.5% of participants have attained a master's degree, while a smaller percentage (1.1%) holds a doctoral degree. The participants also come from diverse academic backgrounds. The majority are from the field of computer science, representing 37.2% of the sample, followed by those from social science disciplines, which account for 16.6%. Business and management fields are also represented, with 11.3% of respondents having backgrounds in these areas.

Table 1.
Demographic Information

		Frequency	**Percent**
Gender	Female	351	57.3
	Male	262	42.7
Age	18 - 21	212	34.6
	22 - 25	214	34.9
	26 - 29	105	17.1
	30 - 33	31	5.1
	34 - 37	21	3.4
	38 - 41	19	3.1
	42 - 45	6	1.0
	46 - 49	3	0.5
	50 and above	2	0.3
Program Level	Diploma	141	23.0
	Bachelor	321	52.4
	Master	144	23.5
	PhD	7	1.1
Field of Study	Engineering (i.e., Civil / Mechanical / Electrical / Chemical, etc)	5.3	8.6
	Business / Management (i.e., Human Resource / Finance / Accounting, etc)	69	11.3
	Social Science (i.e., Sociology /Library Science/ Psychology/ Records and Archives, etc)	102	16.6
	Natural Sciences (i.e., Biology / Chemistry / Physics, etc)	50	8.2
	Humanities (i.e., Psychology / Language / Mass Communication, etc)	31	5.1
	Computing (i.e., Computer Science / Information Technology / Information Systems, etc)	228	37.2
	Mathematics (i.e., Mathematics / Statistics / Actuary, etc)	14	2.3
	Health Science (i.e., Pharmacy / Dentistry / Medicine, etc)	9	1.5
	Art and Design (i.e., Fashion / Graphic / Architecture, etc)	54	8.8
	Others	3	0.5
Year of Study	Year 1	115	18.8
	Year 2	227	37.0
	Year 3	178	29.0
	Year 4	47	7.7
	Year 5	14	2.3
	Year 6	20	3.3
	Year 7	12	2.0

Note: Table generated by the authors based on SPSS analysis.

4.3. Descriptive Analysis

Table 2 presents the results of the descriptive analysis. The mean score for ethical decision-making is 3.963, indicating that participants reported a moderate to high level of ethical decision-making. This suggests that most participants exhibited behaviors and attitudes aligned with ethical principles in their decision-making processes. The small standard deviation indicates responses were closely clustered around the mean, reflecting a relatively consistent level of ethical decision-making among participants. Additionally, the standard deviation of 0.525 signifies limited variability or dispersion around the mean score, further supporting the consistency of participants' ethical decisions. The descriptive analysis for the astute use of AI reveals a mean score of 3.891, indicating an average level of AI usage among participants. On average, participants demonstrated a moderate to high level of astuteness in their use of AI technologies. The standard deviation of 0.602 indicates a moderate degree of variability or dispersion in responses. While most participants exhibited a certain level of skill in using AI astutely, some variation was observed, with a few participants showing higher or lower proficiency in their AI usage.

Table 2.
Descriptive Analysis of Variables.

	Mean	**Standard Deviation**	**Variance**
Ethical Decision Making	3.963	0.525	0.276
Astute Use of AI	3.891	0.603	0.365

Note: Table generated by the authors based on SPSS analysis.

4.4. PLS-SEM Analysis

PLS-SEM analysis involves two main assessments: the measurement model assessment and the structural model assessment. The measurement model assessment, as shown in Figure 2, evaluates the validity and reliability of the constructs included in the model. In this study, convergent validity was established through rigorous evaluation criteria. Specifically, all factor loadings, as shown in Table 3, exceeded the threshold of 0.6, indicating strong relationships between the latent constructs and their observed indicators. Composite reliability values surpassed 0.7, demonstrating the internal consistency and reliability of the measurement model [46]. Furthermore, the average variance extracted (AVE) values exceeded 0.5, indicating that the variance captured by the latent constructs was greater than the variance due to measurement error.

Table 3.
Factor Loading, Composite Reliability, and Average Variance Extracted

Construct	**Item Code**	**Item Statement**	**Factor Loading**	**Composite Reliability (CR**	**Average Variance Extracted (AVE)**
Ethical Decision Making	MS2	I often think about the impact of my actions on others before making decisions	0.668	0.948	0.504
	MS3	I pay attention to the ethical aspects of situations in my daily life	0.713		
	MS4	I try to understand the perspectives of others in ethical dilemmas	0.739		
	MS5	Recognizing ethical issues is important for making responsible choices	0.692		
	MJ2	I try to follow ethical principles, even if it's inconvenient for me	0.727		
	MJ3	I think about the potential consequences of my decisions on others	0.707		
	MJ4	I believe in doing what is ethically right, even if it goes against personal interests	0.705		
	MJ5	I make decisions based on what I believe is morally acceptable	0.613		

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Construct	Item Code	Item Statement	Factor Loading	Composite Reliability (CR	Average Variance Extracted (AVE)
	MM1	I feel internally driven to act in a way that aligns with my ethical beliefs	0.664		
	MM2	Even when it's challenging, I am motivated to follow through on my ethical judgments.	0.719		
	MM3	I understand the importance of sticking to ethical principles for motivating ethical behavior.	0.773		
	MM4	I consistently try to act in accordance with my ethical beliefs and principles.	0.748		
	MM5	I find personal satisfaction in acting ethically, regardless of external rewards.	0.631		
	MC1	I value the development of enduring moral virtues as a guide for ethical behavior.	0.749		
	MC2	Consistently behaving ethically over time is important to me	0.708		
	MC3	I believe having a strong moral character is essential in making ethical decisions.	0.750		
	MC4	Others would describe me as someone with a strong moral character.	0.674		
	MC5	Upholding ethical standards is a consistent part of my actions and decisions.	0.774		
Astute Use of AI	BU1	I effectively manage my time when engaging with AI technologies for different activities.	0.609	0.947	0.547
	BU2	I am able to allocate my time wisely between various AI-related tasks.	0.664		
	BU3	I maintain a healthy balance between online and offline activities involving AI.	0.707		
	BU4	I prioritize my AI-related activities to ensure balanced use throughout the day.	0.724		
	BU5	I am conscious of the time I spend on AI-related tasks and adjust my usage for a balanced approach.	0.767		
	HU1	I pay attention to how my use of AI technologies affects my physical health	0.711		
	HU2	I ensure that my engagement with AI platforms positively contributes to my mental well-being.	0.784		
	HU3	I take breaks and manage screen time to maintain a healthy AI-related routine.	0.786		
	HU4	I am mindful of the potential impact of AI use on my overall health and make adjustments accordingly.	0.759		
	HU5	I prioritize a healthy relationship with AI technologies, considering both physical and mental aspects.	0.785		
	CU1	I use AI technologies to engage positively with others in online communities	0.787		
	CU2	I contribute to online discussions constructively and respectfully using AI.	0.737		
	CU3	I am mindful of ethical considerations when using AI technologies for social engagement.	0.733		
	CU4	I leverage AI platforms to participate in community-based projects or initiatives	0.766		
	CU5	I use AI technologies to positively impact society, promoting civic values and awareness.	0.749		

Note: Table generated by the authors based on Smart PLS analysis.

Figure 2.
Graphical output of PLS-SEM measurement model assessment.

Discriminant validity was assessed using the Fornell-Larcker criterion (Table 4), which compares the square root of the AVE values with the correlations between constructs. The results confirmed discriminant validity, as the square root of the AVE for each construct was greater than its correlations with other constructs. This ensures that each construct measures a distinct underlying concept, demonstrating discriminant validity.

Table 4.
Fornell and Larcker Discriminant Validity.

	Astute Use of AI	Ethical Decision Making
Astute Use of AI	0.739	
Ethical Decision Making	0.685	0.710

Note: Table generated by the authors based on Smart PLS analysis.

The results of the path analysis presented in Table 5 indicate a significant and positive relationship between ethical decision-making and the astute use of AI. The standardized beta coefficient, which represents the regression weight of the path, was found to be 0.685. This indicates that for every one-unit increase in ethical decision-making, there is a corresponding increase of 0.685 units in astute AI use. The associated t-value of 17.623 suggests that this relationship is highly statistically significant, with a p-value of less than 0.001, providing strong support for the hypothesis. Furthermore, the R-square value of 0.469 indicates that 46.9% of the variance in astute AI use can be explained by ethical decision-making, demonstrating that a substantial proportion of the variability in the dependent variable is accounted for by the independent variable [47]. Additionally, the effect size (f-square) of 0.883 indicates a large effect. Moreover, the Q-square value of 0.255, obtained through blindfolding validation, indicates that the model has predictive relevance beyond chance.

Table 5.
Path Analysis.

	β	t-value	p-value	R^2	f^2	Q^2
Ethical Decision Making → Astute Use of AI	0.685	17.623	<0.001	0.469	0.883	0.255

Note: Table generated by the authors based on Smart PLS analysis.

5. Discussion

5.1. Discussion Related to RO1

The finding related to RO1 suggests that most participants in the study made ethical decisions in line with Rest's Model [11]. This indicates that they considered the consequences of their actions, followed their conscience, and took responsibility for their decisions. A mean score approaching 4 on a scale of 1 to 5 implies that participants generally made ethical choices in various situations, demonstrating awareness of moral issues and care in making decisions to do the right thing. This finding highlights the importance of ethics in decision-making, resonating with Rest's Model's dimensions of moral sensitivity, moral judgment, moral motivation, and moral character [17]. Moral sensitivity, which involves recognizing ethical issues, aligns with participants' ability to identify ethical dilemmas in their use of AI technologies. This capacity to recognize moral issues has been identified as a key skill in navigating complex technological environments [19].

Moral judgment, the ability to reason through ethical dilemmas and decide the appropriate course of action, was evident in the participants' ethical choices. This supports earlier findings emphasizing the importance of ethical reasoning in maintaining integrity when using digital tools, especially AI [48]. Their moral motivation, or willingness to prioritize ethical values over personal interests or external pressures, also points to their strong commitment to upholding ethical standards, aligning with observations by Daniel et al. [16] regarding the role of ethical motivation in decision-making. Moral character, which reflects consistency in ethical behavior over time, was also displayed by participants. This competence in ethical decision-making, as suggested by Chauncey and McKenna [28], is essential for personal integrity and societal well-being. Their emphasis on the role of ethical behavior in fostering trust and responsibility further reinforces the need for continued emphasis on ethical education and awareness initiatives.

5.2. Discussion Related to RO2

The findings related to RO2 indicate an average level of astute AI usage among participants, aligning with the three dimensions of astute use: balanced use, healthy use, and civic use [29]. This suggests that participants were generally adept at using AI technologies in a balanced and healthy way, and they also demonstrated a capacity for utilizing AI to benefit society. Balance use, as noted by Baroni et al. [30], involves managing time spent on AI-related activities to prevent over-reliance on technology while maintaining productivity, which was evident in the participants' ability to strike a balance between AI usage and offline tasks. The mean score reflects participants' overall competence in these three dimensions, balancing their AI usage, maintaining healthy usage patterns, and engaging in civic-minded AI practices. This aligns with the framework of digital intelligence, which emphasizes not only technical proficiency but also the ability to make ethical and responsible use of digital tools [20]. Participants demonstrated an awareness of digital well-being, similar to the findings by Kosasi et al. [34], which stresses that a balanced approach to digital consumption is key to avoiding burnout and negative consequences. While participants generally used AI in a thoughtful and responsible manner, there is still room for improvement in specific areas. For instance, adopting strategies that encourage balanced use, such as setting limits and managing screen time, could enhance participants' ability to avoid overuse [48]. Additionally, promoting healthy use habits is crucial for sustaining mental well-being. Practices such as taking breaks and prioritizing emotional health when engaging with AI are essential in maintaining a productive and fulfilling relationship with Chiu et al. [33].

5.3. Discussion Related to RO3

Overall, the results of the path analysis suggest that there is a positive relationship between ethical decision-making and astute use of AI, supporting Rest's Four-Component Model [11], which emphasizes the importance of moral sensitivity, judgment, motivation, and character in guiding ethical behavior. This finding indicates that individuals proficient in making ethical decisions are more likely to use AI responsibly. People demonstrating higher levels of ethical decision-making tend to be more careful and thoughtful in their actions, including their interactions with AI technologies [17]. This is consistent with prior research, which links ethical decision-making with responsible use of technology, particularly AI [28].

The significant positive relationship between ethical decision-making and astute AI usage suggests that individuals who are more ethical are better equipped to weigh the potential risks and benefits of AI technologies and take proactive steps to mitigate those risks. As noted by Barros et al. [48], understanding the ethical implications of AI is essential for aligning technology usage with personal and societal values. This awareness ensures that AI is utilized in ways that promote fairness and minimize harm, reinforcing the role of ethics as a moral compass that guides responsible AI usage. This finding implies that a strong ethical foundation is crucial for the responsible adoption of AI. It enables individuals to make informed and conscientious decisions about how to engage with AI, ensuring that it is used in ways that benefit society as a whole [19]. Ethical AI usage, as emphasized by Elmessiry et al. [10], involves not only recognizing the potential dangers of AI but also ensuring that decisions are aligned with broader societal goals, such as promoting digital literacy and upholding human rights.

6. Conclusion

Based on the results presented above, the study makes several significant contributions to the field of ethics and AI utilization. Firstly, the findings highlight the positive relationship between ethical decision-making and the astute use of AI among participants, underscoring the importance of ethical considerations in shaping individuals' AI usage behaviors. This enhances our understanding of the ethical dimensions of AI adoption and usage, emphasizing the need for ethical awareness and education initiatives in AI contexts. Additionally, the study provides insights into the three dimensions of astute AI usage, balanced use, healthy use, and civic use, and their relationship with ethical decision-making, enriching our understanding of the factors that influence responsible AI utilization.

The implications of the study extend to both practice and theory. From a practical standpoint, the study offers valuable insights for stakeholders such as policymakers, educators, and practitioners involved in AI governance and regulation. By emphasizing the importance of promoting ethical awareness and responsible AI practices, the study underscores the need for developing and implementing policies that foster ethical AI adoption and use across various contexts. From a theoretical perspective, the findings contribute significantly to existing literature on ethics and technology by empirically demonstrating the relationship between ethical decision-making and AI utilization behaviors. This enhances our understanding of the ethical considerations inherent in AI adoption and use, providing directions for future research in this area.

However, this research is not without its limitations. Firstly, the research was conducted within a specific context and may not be fully generalizable to other populations or settings. The use of a convenience sampling technique is another reason why the findings cannot be generalized, especially to broader populations. In addition, the use of self-reported measures and cross-sectional data may introduce response biases and limit the ability to establish causality. Furthermore, the study focused on university students, and the findings may not fully capture the perspectives of other demographic groups or AI user populations. Considering these limitations, several future research directions are suggested. Firstly, instead of using cross-sectional data collection, future studies could employ longitudinal designs that incorporate diverse participant samples. Additionally, future research could also use objective measures, such as the amount of time spent using AI, the number, types, and frequency of AI applications used. Lastly, employing probability sampling methods, such as simple random sampling or systematic random sampling, would enable the research findings to be more generalizable to larger populations.

Institutional Review Board Statement:

This study was conducted in accordance with institutional ethical standards. Participation was entirely voluntary, and informed consent was obtained from all respondents before data collection. Participants were informed about the study's purpose, their right to withdraw at any time, and the assurance of anonymity and confidentiality. No identifying information was collected. Consent to publish aggregated and anonymized findings was obtained as part of the informed consent process.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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