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Engineering students' relationships with new technology and the use of AI

The aim of our research was to explore university-level engineering students' attitudes toward new technology and relationships with AI. We administered the Technology Readiness Index 2.0 and a proprietary measurement tool adapted to AI (i.e., TRI AI) in a sample of 361 engineering students. According to the results, students are generally open to AI, though their attitudes differ according to their engineering specialization and digital competencies. Greater digital proficiency was closely related to greater knowledge about AI, greater confidence with AI, and less resistance to AI. Cluster analysis, revealing four types of attitudes, clarified that attitude toward AI differs from attitude toward technology in general. Meanwhile, moderate correlations between TRI AI and TRI scores indicated the need for an AI-specific approach when measuring students' readiness and attitudes toward AI. The results can be used to develop targeted educational and communication strategies that take into account students' varying degrees of receptiveness to technology.

Keywords: *relationship to new technology, use of AI, empirical research, technical university student*

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1. Introduction: Social aspects of the spread of new technology

In human environments, the general attitude toward recent achievements in technological development is an important factor in the effective use of new tools, as confirmed by international research conducted in different social groups and different disciplines. The success of innovation depends on how end users adopt the new technology and how they behave.

For example, online commercial activities on mobile devices are already an integral part of people's daily lives. Although the process of buying as well as selling goods and services is simpler and more enjoyable, the lack of limitations in time and space still have negative effects on consumer behavior (Syamfithriani et al. 2021). In another example, specifically regarding the difficulties of introducing new IT procedures in healthcare, have reported, sometimes in reference to additional studies (Michel-Verkerke, Stegwee and Spil 2015; Fanta, Pretorius and Erasmus 2018), that although IT tools can raise the quality of healthcare and offer a viable solution in developing countries and regions in conflict, the sustainability of electronic health continues to pose challenges. Even though many eHealth experiments are conducted in those countries, those projects cannot be fully implemented due to the attitude among locals.

In other work, the effects of the relationship to technology on social relations have also been analyzed (Pires, da Costa Filho and Junior 2024). Although the use of social media is widespread, the platforms, how they are used, and the motivations for using them among users differ just as widely. The differences in perceptions about social media strongly affect the behavior related to the use of those platforms. To be sure, the importance of such behavior is enormous, for social media posts can transform social relations, the current social environment, and relationships. Meanwhile, in social science research, Dolmark et al. (2022) have found empirical evidence that an individual's beliefs about technology affect learning behavior and the ability to absorb knowledge. Their research among university students has additionally confirmed the causal relationship between technological beliefs and an individual's learning ability.

In the context of attitudes toward new technology, the emergence and spread of AI can be considered to constitute one of the major social challenges of the current era. Indeed, due to its rapid development, AI is widely used in nearly every aspect of daily life. However, the idea that machines can behave similarly to humans and make decisions instead of humans scares many and has raised diverse concerns and prompted various debates. According to Héder (2020), calls for social control over AI have risen steadily since the mid-20th century. In a study by Douali, Selmaoui, and Bouab (2022), most educators interviewed were seriously concerned about the future use of AI, especially its impact on early childhood development, but slightly optimistic about its use in technical services and in assisting with teaching-related tasks. Dong et al. (2024) also examined fears about the emergence of AI in different professions across 20 countries in a sample with tens of thousands of people. Their research, focusing on the psychological characteristics of people in different occupations, confirmed a psychological model that can predict fears about AI in different countries and professional fields.

The emergence of AI presents considerable challenges to higher education as well, including fears among students. In research by Phong et al. (2024), attitudes toward AI significantly affected students' academic outcomes, and students had concerns that they would have to explain themselves if they used AI applications in learning environments. Despite those worries, knowledge of the benefits and challenges associated with using AI, as well as being skilled in doing so, is key for higher education institutions in terms of integrating AI and modern technology into the curriculum so that universities can create a learning environment that enhances educational outcomes.

What all the above suggests is that understanding users' attitudes toward new technology and internal drivers for using it plays a central role in the success of new technology to be introduced, including AI. Mapping the attitudes and technical preparedness of the new technology's stakeholders can thus be viewed as an important condition in the process of its introduction and implementation. Along those lines, a key question is which psychological construct provides the most appropriate framework for interpreting individuals' relationships with new technology. According to McLean (2003), attitudes, beliefs, and values correlate, but researchers have different theories as to which emerges and acts first and which derives from the other. Because humans learn about their values, beliefs, and attitudes through interactions with others, with an *attitude* defined as an individual's direct willingness to evaluate or respond to an abstract concept or object. Attitudes can change easily and often. By contrast, *beliefs* are ideas based on past experiences, not necessarily logic or facts. Beliefs often serve as a frame of reference through which people interpret their worlds. Last, *values* are basic concepts and ideas about what individuals consider to be good or bad, right or wrong, or what is worth a sacrifice. Similar to beliefs, values are not based on empirical research or rational thinking, and they are even more resistant to change than beliefs. For an individual to change their values, they may need a transformative life experience. Thus, when examining the relationship of individuals to innovative technology and AI, their attitudes, views, and beliefs should be interpreted as a complex, compound concept.

In our study, we evaluated the openness of individuals, specifically university-level engineering students, to new technology and AI in terms of affective, cognitive, and conative factors as well as their beliefs. We focused on their knowledge of AI-related concepts and, in relation to using new technology, specifically AI, their confidence, their optimism and innovativeness, their sense of discomfort and insecurity, and their interest and openness.

2. Purpose, research questions, and methods

Individuals with a high readiness to use technology—that is, "technology readiness"—are more likely to be open to using new technology, including AI. Technology readiness positively affects trust in the advantages of technology and thus the likelihood of its use by the individual.

Along those lines, in our study we aimed to assess the general technology readiness of students at a technical university, their relationship with using AI, and the connection between the two trends. In the process, we sought to answer three questions:

Q1. What are students' relationships with technology in general?

Q2. What are students' relationships with using AI?

Q3. What is the connection between students' relationship to technology in general and their use of AI?

Three measurement tools were used in the study:

1. A questionnaire that we developed to collect the sociodemographic data of respondents and gain insights into their digital and language competencies;
2. The 16-item Technology Readiness Index 2.0 (TRI) questionnaire to examine students' relationship with the daily use of new technology; and
3. The Technology Readiness Index for Artificial Intelligence (TRI AI), another questionnaire that we developed to examine university students' relationship with the daily use of AI.

The development of the TRI, one of the best-known tools for measuring technology readiness, can be attributed to Parasuraman (2000). Meanwhile, the 36 items of the four-dimensional TRI were later developed to measure people's willingness to adopt and use an innovative technology. Among the four dimensions of the TRI—optimism, innovation, insecurity, and discomfort—optimism and innovation are motivating factors for technology readiness, while discomfort and insecurity are inhibiting factors (Parasuraman and Colby 2015). The TRI is a measure of the extent to which the user will be able to master the given technology and use it to perform their daily tasks and achieve their goals. Beyond that, the TRI provides an opportunity to form user groups and thus rationalize the process of introducing a new technology; in Parasuraman and Colby's study, those groups were skeptics, explorers, laggards, pioneers, and paranoiacs. The TRI is also widely used to gauge individuals' predisposition to using new technology and can characterize their general readiness to adopt the technology, especially based on individual personality. Because the introduction of new technology causes both positive and negative emotions, different characteristics and cultural beliefs play a significant role in terms of its use (Klaus 2013; Yang, Kim and Yoo 2013). In that sense, the TRI does not measure intention or behavior but does provides information about the individual's technology readiness (Abu-Assi, Al-Dmour and Abu-Assi 2014).

By comparison, our questionnaire was developed to investigate the relationship with using AI (i.e., TRI-AI), including in terms of several components of attitude:

- □ Cognitive factors: Knowledge of AI
- □ Beliefs: Views on AI
- □ Affective factors: Emotions related to using AI
- □ Conative factors: Experiences and actions related to using AI

Reflecting on the complexity of internal driving forces, we sought to examine engineering students' relationship with new technology and AI in order to reveal the distinct components underlying their attitudes. Based on the degree of internal conflict, the findings suggest changes in attitudes, which may require pedagogical solutions in engineering training programs.

Constructs measured by the TRI and TRI AI	Technology Readiness Index (TRI)	Technology Readiness Index for Artificial Intelligence (TRI AI)
Knowledge of AI-related concepts	-	0.884
Confident use	-	0.839
Optimism	0.701	0.924
Innovation	0.737	0.795
Discomfort	0.612	0.864
Insecurity	0.594	0.896
Interest and openness	-	0.863

Table 1. Reliability of the two measurement tools

Based on the Cronbach's alpha factors, both measurement tools were reliable (Table 1). In the TRI's case, the consistency of constructs was also checked with Amos 23 (IBM), and the model fit fairly well with the expected structure (RMSEA = 0.057, TLI = 0.874, CFI = 0.897, AGFI = 0.917)[1]. In the TRI AI's case, the internal consistency of all seven factors was excellent.

3. Results

3.1. Sample

Of the 361 technical university students who participated in our study, 270 were men (74.79%), and 91 were women (25.21%). Their mean age was 22.84 years (*Mdn* = 22 years, *mode* = 19 years)—314 were 25 years or younger (86.98%), whereas all others were older—and 264 were currently enrolled in BSc programs (73.13%) and 97 in MSc programs (26.87%). Of the participants in the BSc programs, 225 graduated from a high school (85.22%) and 34 graduated from a technical school (12.88%). Most students were enrolled in engineering, while a smaller group was enrolled in social science or natural science programs (Figure 1).

[1] (Root mean square error of approximation [RMSEA] = 0.057, Tucker–Lewis index [TLI] = 0.874, comparative fit index [CFI] = 0.897, adjusted goodness-of-fit index [AGFI] = 0.917)

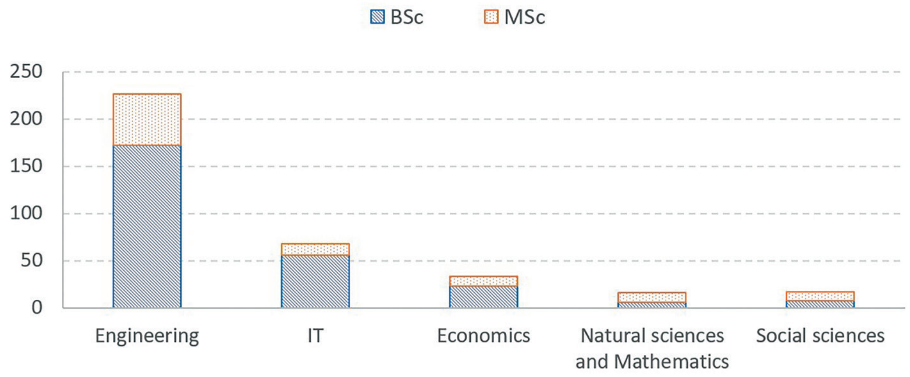

Figure 1. Distribution of students by academic level and fields of training

Of the students enrolled in MSc programs, with an expected study period of 2 years, 35 started their studies a year ago (36.08%), 36 started 2 years ago (37.11%), and 26 started more than 2 years ago (26.81%). Most participants in the BSc program, with an expected study period of 3.5 years, had been studying at the university for 1–4 years (Figure 2).

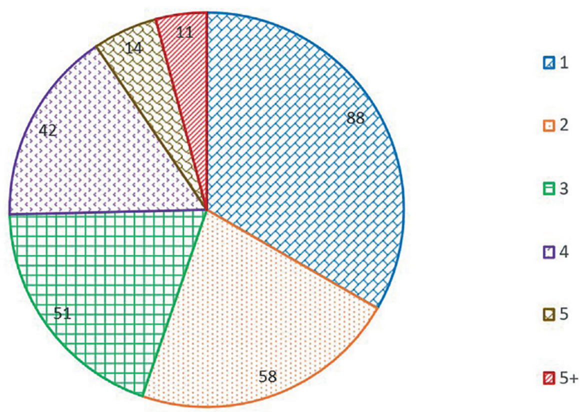

Figure 2. The time spent by BSc students in their fields of training

Regarding the use of technology, the level of foreign language and digital competencies is especially important. In the case of foreign-language competencies, we asked about English and German skills. The students had to evaluate their own language skills on a 7-point Likert scale from 1 (*completely missing*) to 7 (*excellent*). The studied subcompetencies were reading comprehension, listening comprehension, and speaking. In English, there was a slightly weaker result in speaking (M = 5.15, SD = 1.376) but very good results in reading comprehension (M = 6.08, SD = 1.041), which is arguably more important in learning new technology, and in listening comprehension (M = 5.73, SD = 1.170), as shown in Figure 3. Approximately 10%–15% of students communicated at an acceptable level in German.

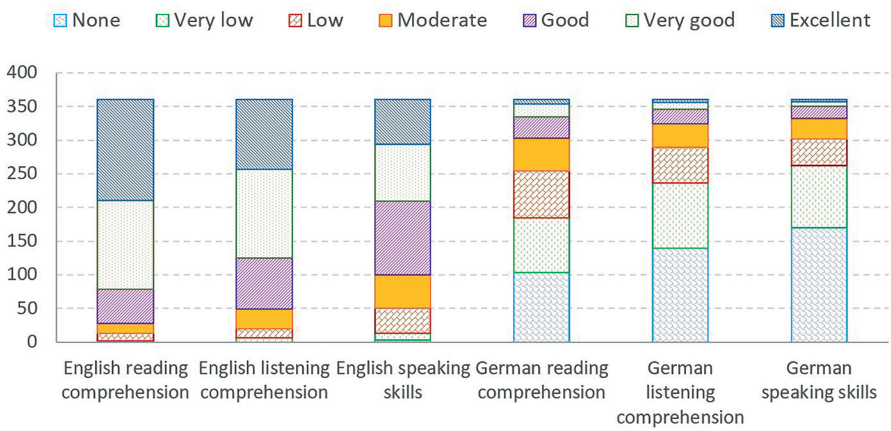

Figure 3. Development levels of students' foreign-language competencies

Based on the above, it can be established that the vast majority of students had the language competencies required for using technology, primarily in English.

The background questionnaire section on digital competencies had 21 items, which focused on questions related to searching, managing, generating, and protecting data and content as well as eliminating technical issues and complying with ethical standards. In that case, the students also had to evaluate their own competencies on a 7-point Likert scale.

Summing up all subcompetencies, we determined the development of students' digital competencies on a scale ranging from 20 to 147 scale (M = 108.87, SD = 19.420, 95% CI: 106.86, 110.88; SEM = 1.022, Mdn = 111, min. = 46; max. = 147). In terms of development level, we formed five categories: undeveloped (i.e., 21–46 points; n = 1), below average (i.e., 47–71 points; n = 11), average or moderately developed (i.e., 72–97 points; n = 83), above average (i.e., 98–123 points; n = 179), and developed (i.e., 124–147 points; n = 87). The vast majority of students had the competencies required for applying digital techniques and technology.

In the case of foreign-language competencies, we evaluated both languages and used the higher score of the two. The variable created thus expressed the level at which students can interpret the descriptions related to using technology in a foreign language and communicating with the technology. The score available was between 3 and 21. For students who scored less than 12 points, we considered their language competency as being insufficient to interpret the descriptions related to the technology. Except for 32 students (8.86%), students generally possessed sufficient foreign-language competency to master new technology.

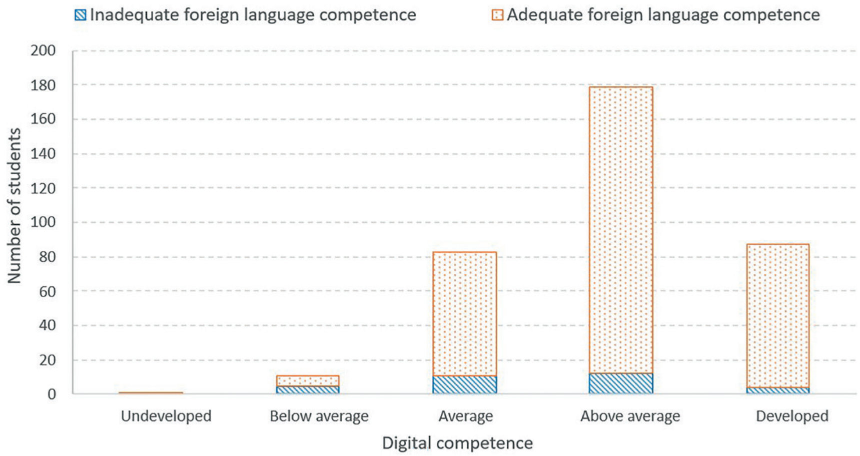

Figure 4. Relationship between students' digital and foreign-language competencies

We found a significant correlation between foreign-language and digital competencies ($\chi 2 = 23.301$, $p < 0.001$); the strength of the symmetric relationship was Cramer's V (i.e., 0.254), which can be considered to be weak to moderate. Above-average digital competencies were also accompanied by appropriate foreign-language competencies; thus the cognitive prerequisites for the attitude toward the use of new technology are appropriate (Figure 4).

3.2. Engineering students' relationships with technology in general

None of the four factors followed a normal distribution, as the descriptive statistical indicators summarized in Table 2 show. Only the insecurity factor indicated a significant difference compared with the others. On a 4–20 scale, this was the lowest-scoring factor, that is, students felt less insecure about using new technology, while discomfort was the highest. In other words, those two negative factors appeared to be opposite. There was no significant difference between the two positive factors. Values close to optimism, innovation, and discomfort indicated that students were fundamentally positive about new technology and willing to use it, even if it involved some discomfort. That finding indicates that the predisposition to accept and minor inhibitions were balanced. Low insecurity indicated that students trusted technology and did not fear that it would be unpredictable.

	Optimism	Innovation	Discomfort	Insecurity	TRI total
M	14.58	14.86	15.31	10.90	55.65
SEM	0.159	0.180	0.146	0.163	0.463
Lower 95% CI	14.27	14.51	15.03	10.58	54.74
Upper 95% CI	14.89	15.22	15.60	11.22	56.56
SD	3.030	3.421	2.767	3.103	8.789
Variance	9.183	11.703	7.655	9.626	77.239
25%	13	13	14	9	50
50%	15	15	16	11	57
75%	17	17	17	13	62

Note. TRI: Technology Readiness Index; CI: confidence interval.

Table 2. Descriptive statistical indicators of factors of technology readiness

We also found a moderate relationship between the four subfactors, with innovation standing out as having the weakest relationship with the two negative factors (i.e., discomfort and insecurity), as shown in Table 3. Optimism and innovation moved together but were also fairly separated from each other. The negative dimensions were also closely correlated but affected innovative predisposition less.

	Optimism	Innovation	Discomfort	Insecurity
Optimism		0.451**	0.352**	0.439**
Innovation			0.173**	0.221**
Discomfort				0.375**
Insecurity				

** Correlation is significant at the 0.01 level (2-tailed).

Table 3. Correlation system between the subfactors of the Technology Readiness Index

All the above suggests that the technical university students were mature, technology adopters, "technology consumers," but also critical users. They were not naively optimistic, not afraid of technology, willing to train themselves, could learn independently, and had confidence in using technology. They were also open and cooperative and able to tolerate minor discomfort.

Total TRI scores can range from 16 to 80. In our study, the mean value was slightly higher than the average (Table 2), and unlike the subfactors, the variable followed the normal distribution according to permissive conditions of skewness (SES = −1.805) and kurtosis (SEK = 0.535; Sajtos–Mitev, 2007, 95). Regarding the relationship to technology, we formed three categories (Figure 5): distant (16–37 points; n = 8), prudent and cautious (38–59 points; n = 223 people), and open and interested (60–80 points; n = 130).

We analyzed those categories from several perspectives. When examining them based on the students' fields of expertise, the distant relationship was not or hardly typical in the field of IT or engineering, with the highest proportion occurring among students in the social sciences, as is understandable, for they encounter less technology during their studies than, for instance, engineers. It is also unsurprising that computer scientists were the most open, but perhaps it comes as a surprise that economics students were ahead of the engineering majors. That outcome may be because students in economics also use various forms of technology on a daily basis (e.g., in statistical programs, business simulations, and AI) and given the digitalization of the business world (e.g., e-commerce and digital marketing), such students may be more motivated (i.e., optimistic) in terms of embracing technological innovations. Engineering students may be more technically competent but are also less open to or enthusiastic about new technology, instead preferring to approach them pragmatically and critically.

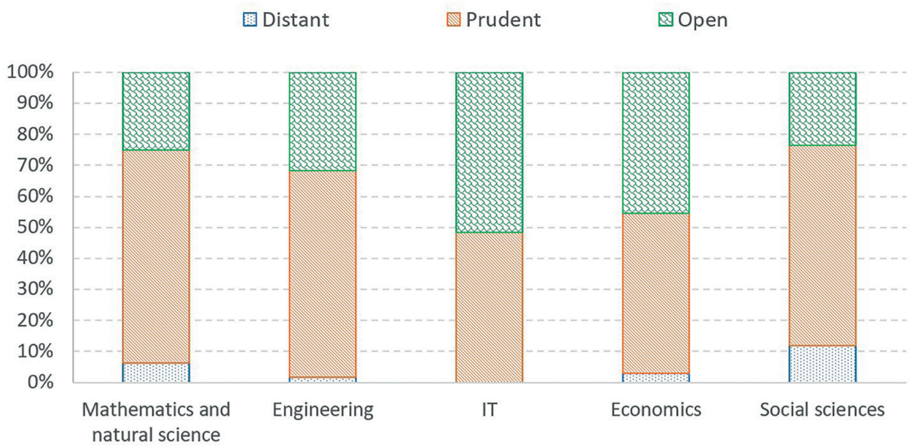

Figure 5. Categories by relationship to technology

Examining the subfactors, a significant difference emerged between the three departments except for the feeling of discomfort (Table 4). IT students showed the greatest technological openness, for their optimism and innovation were also outstanding, which is understandable given the strong technological orientation of their field. Economics students showed similar optimism, though their innovation was far lower, suggesting that they recognized technology's usefulness more than they actively sought new solutions. The results for the engineering students, meanwhile, suggest that although they were less enthusiastic—their optimism was lower—they were also more confident in managing technology (i.e., had a lower sense of insecurity), which likely relates to the nature of their studies.

Academic program	Optimism	Innovation	Discomfort	Insecurity
	M (*SD*)			
Engineering	14.32 (3.064)	14.61 (3.414)	15.18 (2.722)	10.61 (2.936)
IT	15.46 (2.690)	16.94 (2.143)	15.82 (2.562)	11.65 (3.318)
Economics	15.48 (2.575)	13.58 (3.437)	15.76 (3.052)	11.91 (3.176)
$\chi 2$	8.705	33.210	3.859	9.832
p	0.013	0.000	0.145	0.007

Table 4. Comparison of subfactors of the Technology Readiness Index for the programs analyzed

In addition to academic program, the other factor possibly associated with the relationship to technology was digital competencies. The two variables showed a significant correlation (Fisher's exact test= 52.913; $p < 0.05$), the linear trend was highly significant ($p < 0.05$), and the standardized statistics (6.747) confirmed a likely directed, growing relationship between the variables. Thus, a direct correlation seems to exist between students' relationship to technology and their digital competencies (η = 0.359), as shown in Figure 6.

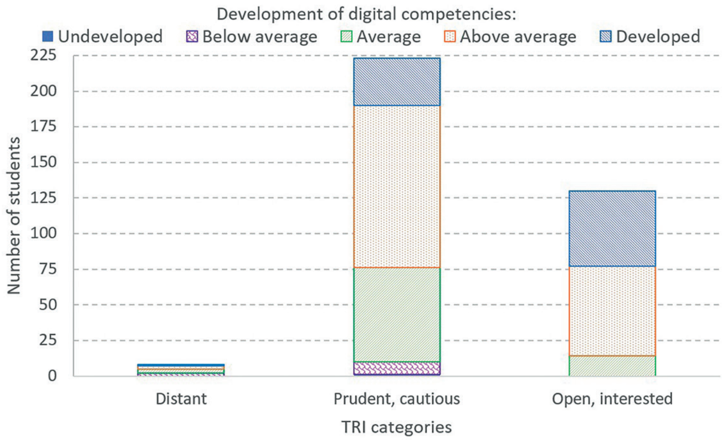

Figure 6. Correlation between the development of the Technology Readiness Index and digital competencies

Using the digital (i.e., DigComp) and foreign language (i.e., LangComp) competencies, we set up the following model for the relationship to technology:

$$\text{TRI} = 27.582 + 0.213 \times \text{DigComp} + 0.282 \times \text{LangComp}$$ [2]

The development of both language and digital competencies significantly improved the relationship to technology. However, the model's explanatory power was not very high (adj. $R2 = 0.262$), meaning that other factors also affected the relationship to technology. The highest level of education and the number of semesters completed at the university did not, whereas the student's academic program only slightly improved the explanatory power (adj. $R2 = 0.283$). The above model had some explanatory power ($F = 65.031$; $p < 0.05$) despite being only moderate. Based on the standardized β, digital competencies seemed to explain a greater proportion (β = 0.472) of the variance in TRI score than foreign-language competencies (β = 0.103).

3.3. Engineering students' use of AI

Several AI applications are available that technical university students can use in their daily work and in fulfilling their academic requirements. At the beginning of the questionnaire, we asked about the frequency of their use.

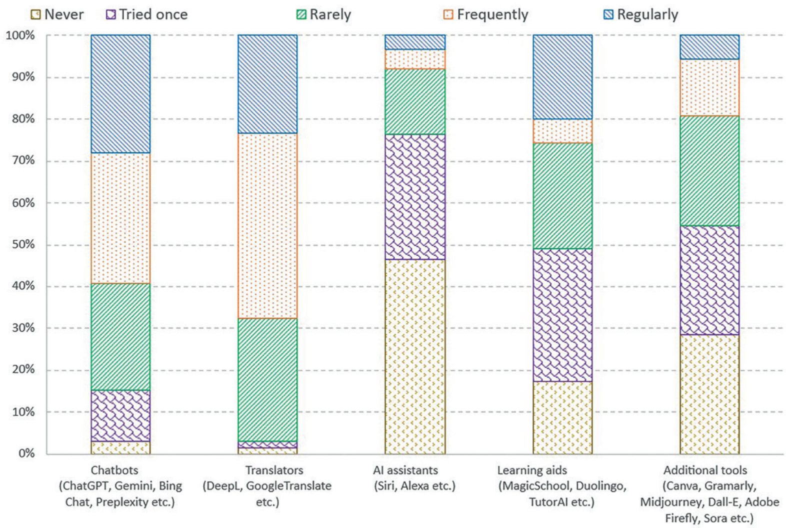

Figure 7. Students' use of AI applications

[2] *Note.* DigComp: 21–147; LangComp: 3–21; Constant: $t = 10.260$, $p < 0.05$, 95% CI: 22.295, 32.869; DigComp: $t = 9.780$; $p < 0.05$, 95% CI: 0.171, 0.256; LangComp: $t = 2.130$; $p = 0.034$, 95% CI: 0.022, 0.543. The distribution of standardized error terms was normal ($p = 0.132$), and the conditions of homoskedasticity and multicollinearity were met.

The most widely used applications among students (60%–70%) were chatbots and translators, which most students reported using frequently or regularly. Learning aids were less familiar to students (Figure 7), meaning that faculty members need to promote opportunities to use those aids among students in the future. In terms of majors, no significant difference arose in the opinions of students, and in terms of time spent at the university, only the use of translators ($H = 10.256$; $p = 0.36$) showed significant difference. As the students progressed in their studies, they seemed to increasingly use various translator applications.

We compared the three most common types of applications (i.e., chatbots, translators, and learning aids) with students' relationship to new, innovative technical tools. Based on the results, the students' technological susceptibility showed a significant correlation with the use of certain AI-based applications. There were also significant differences in the frequency of the use of chatbots ($\chi^2 = 60.950$; $p < 0.001$; $\eta = 0.375$) and translators ($\chi^2 = 18.642$; $p = 0.017$; $\eta = 0.231$) along the three types of technological attitudes developed on the basis of the TRI 2.0 (i.e., distant, prudent and cautious, and open and interested). Those correlations suggest that the more open and technologically inclusive a student is, the more committed they are to using those AI-based tools frequently. By contrast, we could not detect any significant relationship in the case of learning aids ($\chi^2 = 7.611$; $p > 0.05$), which may indicate that external (e.g., study) factors were primarily behind their use, not students' openness to technology. The results support the idea that technological attitudes have a significant impact on the independent, motivated use of AI applications (Figure 8).

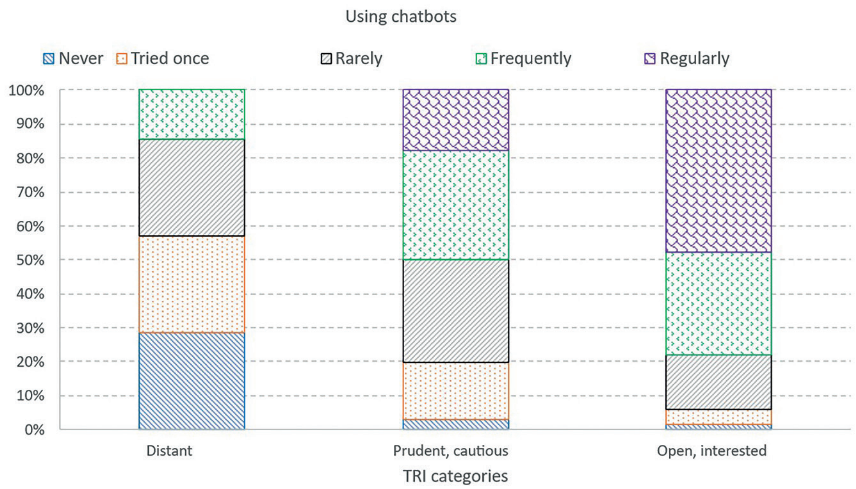

Figure 8. Link between the relationship to technology and the frequency of chatbot use

Based on the relationship to new technology, the following findings can be made regarding the frequency of AI-based applications:

- Distant: (1) has high insecurity and discomfort; (2) is skeptical about the capabilities of AI; (3) uses chatbots or translation programs infrequently or not at all; (4) distrusts the decisions of automated systems; (5) seeks out human instead of machine help, especially with translation; (6) uses AI-based tools only as a last resort; and (7) values transparency and human control.
- Prudent and cautious: (1) tries chatbots or translators but only in a known, trusted environment; (2) checks the answers or translations provided by AI; (3) values usability, data protection, and reliability; and (4) uses AI in their studies but always has a human solution as a backup.
- Open and interested: (1) enjoys experimenting with new technology and actively uses AI solutions; (2) uses chatbots and machine translators regularly; (3) is curious about how to better integrate AI in their own work or daily life; and (4) is open to experimentation but monitors quality critically.

3.4. Engineering students' relationship with using AI

To assess students' attitudes toward using AI, we used a proprietary 33-item questionnaire (Table 5), where students had to evaluate the claim related to the AI application on a 5-point Likert scale. While compiling the questionnaire, we started with the TRI model but specified it for the use of AI and added three additional subfactors. Due to the different number of items and for the sake of comparability with the TRI, we calculated with relative scores. The descriptive statistical indicators appear in Table 5. None of the subfactors were normally distributed ($p < 0.001$).

	Items	*M*	*SD*	*SEM*	95% CI, Lower	95% CI, Upper
		Relative values				
Knowledge of AI-related concepts	3	14.45	4.1948	0.2309	13.99	14.91
Confident use	3	15.38	3.5605	0.1960	14.99	15.76
Optimism	6	14.08	3.8756	0.2253	13.64	14.52
Innovation	6	12.29	3.2799	0.1906	11.91	12.66
Discomfort	6	8.26	2.9393	0.1708	7.92	8.60
Insecurity	6	13.65	3.5502	0.2063	13.25	14.06
Interest, openness	3	13.73	4.4644	0.2458	13.24	14.21

Note. CI = confidence interval.

Table 5. Descriptive statistical indicators of the factors of the Technology Readiness Index for AI

Students' technical and cognitive readiness for AI was good (i.e., self-confident when using AI and knowledge of AI-related concepts) but also characterized by only moderate psychological openness (i.e., innovation and optimism). The moderate score for optimism did not indicate excessive commitment to AI, either, while the moderate score for innovation also indicated a follower instead of a pioneer relationship with AI. At the same time, no significant discomfort in relation to AI applications emerged.

Overall, the results suggest that, in technical university education, it seems necessary to increase trust in AI in order to raise awareness of the ethical standards of its application (e.g., to include a related course in the training program and develop the teaching methodology); to emphasize the need for reflective, critical thinking about the future of technology; and finally to develop students' innovation ability (e.g., creative use of AI).

We also examined the factors of the TRI AI according to various background variables and found a significant difference in several cases (Tables 6 and 7). Based on the analysis of the relationship- and knowledge-based differences related to AI, students' fields of expertise seemed to have a significant effect on the differences in the factors of the TRI AI. Students in IT training had the highest level of AI knowledge and felt the least discomfort in using AI. Paradoxically, the greatest insecurity also arose among them, which suggests that they are more aware of the risks and ethical problems associated with using AI owing to their deeper knowledge. Engineering students had similar technical and technological orientations, but their conceptual knowledge was slightly lower, and their sense of discomfort was slightly higher. Economics students, by contrast, had a relatively low level of AI knowledge but were extremely optimistic about the future impacts of technology. Taken together, those results may indicate that positive attitudes are sometimes not based on knowledge but instead on economic and social expectations and idealized visions of the future. At the same time, their sense of insecurity was lower, which may also suggest a less conscious perception of risks.

Academic program	**Knowledge of AI concepts**	**Optimism**	**Discomfort**	**Insecurity**
Engineering	14.35 (3.9839)	13.66 (3.9965)	8.47 (2.9377)	13.67 (3.6059)
IT	16.89 (2.8097)	14.16 (3.8427)	7.04 (2.7660)	14.14 (3.5673)
Economics	13.13 (3.7659)	16.09 (3.3878)	7.92 (2.3266)	11.87 (3.1921)
Kruskal–Wallis H	29.234	7.004	11.548	6.884
p	<0.001	0.030	0.003	0.032

Note. Means and standard deviations appear in parentheses.

Table 6. Significant differences by major

Digital competencies	Knowledge of AI concepts	Confident use of AI	Discomfort
Below average	7.60 (3.9277)	10.93 (3.8129)	10.47 (2.4954)
Average	12.16 (3.8622)	14.38 (2.8625)	9.37 (2.8232)
Above average	14.96 (3.4670)	15.79 (2.9940)	8.31 (2.9058)
Developed	17.21 (3.1994)	16.96 (3.5758)	7.03 (2.8202)
Kruskal–Wallis H	60.890	26.735	35.026
p	<0.001	<0.001	<0.001

Note. Means and standard deviations appear in parentheses.

Table 7. Significant differences by categories of digital competencies

Students' relationship with the use of AI and their skills were significantly correlated with their self-assessed digital competencies (Table 7). The results clearly indicate that digitally advanced students approach AI technology from a more advantageous position, in terms of knowledge, attitude, and comfort of use.

Understanding the conceptual system of AI is closely related to general digital proficiency. The factor of confident AI use showed a similar trend—that is, individuals with low digital competency felt less comfortable using AI tools, whereas ones with advanced competencies were far more confident. That finding showcases the relationship between practical skills and users' self-confidence. The feeling of discomfort, however, followed a reverse pattern related to the use of AI—that is, there was a higher degree of resistance and discomfort among less digitally competent students, while the value was lower for ones with advanced digital competency, thus indicating greater acceptance and adaptability.

Statistically speaking, all those results were also strongly significant ($p < 0.001$ for all three variables)—that is, not indicative of a random pattern but showing a clear trend that the development of digital competency promotes the acceptance, understanding, and use of AI.

4. Comparison of results

In analyses with data from the 296 students who completed both questionnaires, results obtained with the two measurement tools (Tables 2 and 5) suggest no significant difference between the students' use of AI and use of technology in general. However, moderate differences in innovation and insecurity did arise, along with more significant differences in terms of discomfort.

Even so, there was much less discomfort with AI than with technology in general. That finding suggests that students felt more comfortable in the AI environment than when using other new technology. That result may seem somewhat surprising; however, it should be remembered that the study's sample was students at a technical university.

Insecurity was higher with AI than with general technology—that is, students were not sure how AI will affect their lives or whether it is reliable at all. They reported using it on a cognitive level but still had questions at the level of affective trust. Students used it rather passively and did not feel as though they were sufficiently active creators.

In sum, it can be concluded that students' relationship to AI is not hostile but less enthusiastic and less innovative than with other technology. However, it is also more uncertain, probably due to AI's complexity and novelty. AI-specific factors and general technology factors were related but did not completely overlap (Table 8).

	Relationship between TRI and TRI AI (p = 0.01)
Optimism	0.474
Innovation	0.402
Discomfort	0.455
Insecurity	0.351

Table 8. Relationships between factors of TRI and TRI AI

Those results indicate that students who are generally open to or optimistic about technology are more likely to have positive opinions about AI. By extension, attitude toward AI does not seem to be independent of attitude to technology in general. At the same time, it is also clear that the relationship to AI applications has its own, independent dimension, which cannot be described solely by the general relationship to technology.

AI is not simply a new technology but a phenomenon that triggers an independent relationship framework. The relatively weak correlation with insecurity suggests that other kinds of fears (e.g., ethical and control-related) other than the lack of familiarity also play a role in the relationship to AI.

Based on the relevant four factors of TRI and TRI AI, we determined total scores (i.e., TRI Total and TRI AI Total), which were subjected to cluster analysis, the results of which we separated into four groups (Figure 9).

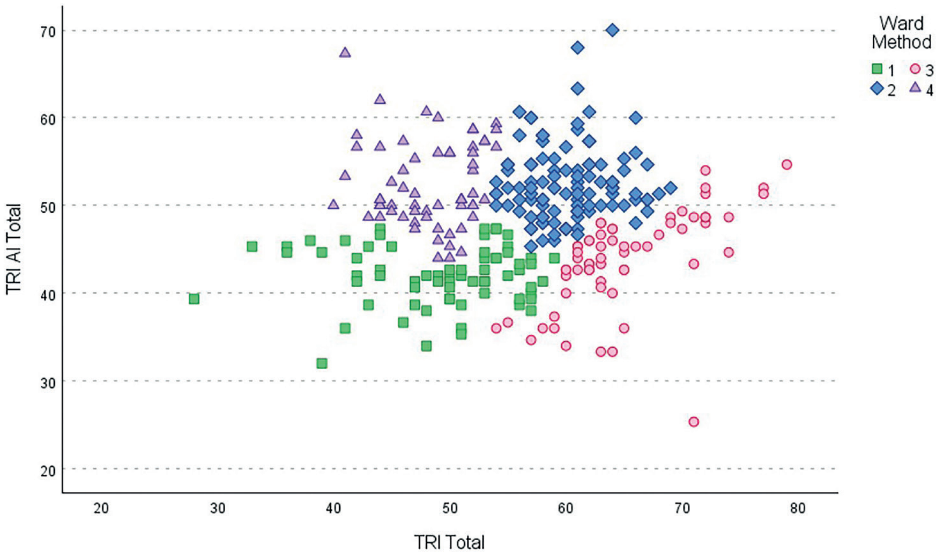

Figure 9. Clusters determined on the basis of TRI and TRI AI scores

The characteristics of the four separate groups are as follows (Table 9):

- Techno and AI sceptic (C1): This group achieved the lowest scores in terms of the relationship to both general technology and AI. Students in the group typically showed low technological receptivity and were skeptical or dismissive of the application options of AI. They were thought to have little experience or else a negative attitude fed by certain fears, insecurity, or lack of knowledge.
- Inclusive to both technology and AI (C2): This cluster was the most highly populated and accounted for nearly one-third of the sample. Its members had high technological affinity and a positive attitude to AI. They were the most open to innovations and were presumably active technology users.
- Open to technology but distant in terms of AI (C3): This cluster's members had a very high level of technological receptivity but were more cautious and prudent in their perception of AI. They were likely to have reservations about the reliability, ethics, or impact of AI.
- Generally distant to technology but open to AI (C4): This group showed a contradictory profile, for they were characterized by a relatively high AI receptivity despite their low overall commitment to technology. They probably lacked a general interest in digital tools or platforms but found AI specifically useful, interesting, and/or exciting, especially if related to their field of expertise.

Clusters via Ward's method		TRI	TRI AI
Techno and AI skeptic (☐)	*M*	49.16	41.98
	SD	6.702	3.374
	N	68	
	Proposed methodology: Practical examples, experience-based learning, presentation of best practices		
Inclusive to both technology and AI (◇)	*M*	60.20	52.56
	SD	3.571	4.396
	N	103	
	Proposed methodology: Involving students in research projects, testing, and mentoring their peers about AI		
Open to technology but distant in terms of AI (○)	*M*	65.10	43.90
	SD	5.506	5.592
	N	62	
	Proposed methodology: Developing students' critical thinking and clarifying ethical and validity issues		
Generally distant to technology but open to AI (△)	*M*	48.21	52.39
	SD	3.716	4.841
	N	63	
	Proposed methodology: Presentation of specific use cases		

Table 9. Key characteristics of clusters

The C2 cluster, which is committed to both areas, included students with diverse IT competencies (i.e., computer science engineers and mechanical engineers), whereas the group that was generally distant to technology but open to AI (i.e., C4) included students in the natural and social sciences.

5. Discussion and conclusion

Relationships to AI at the level of individual attitudes, views, beliefs, knowledge, and digital competency are particularly revealing among technical university students. The TRI AI questionnaire developed in the course of our research and adapted to AI reliably measured students' knowledge of AI concepts, confidence and innovation in using it, optimism toward it, and fears and resistance toward it, embodied in the factors of discomfort and insecurity.

Per our results, students are basically open and interested in AI technology, but such attitudes are significantly differentiated according to their specialization and digital competency. Computer science and engineering students have a higher level of knowledge and self-confidence, but the greatest degree of insecurity occurs among IT professionals, probably due to their awareness arising from their profound knowledge of technology. The optimism of economics students is high, but their knowledge of AI concepts and self-assessed confidence in using it are lower, which may indicate that their vision of AI is based on expectations instead of any foundation of knowledge. The developmental level of digital competencies is closely related for all AI factors examined—that is, higher digital proficiency correlates with higher knowledge, self-confidence, and lower resistance.

Based on our findings, it seems that the relationship of students to AI is generally positive, especially in terms of usability and technical confidence. At the same time, there remains room for improvement in terms of psychological integration and a future-oriented, innovative attitude, for the confidence index and creative openness are more moderate than in the case of the relationship concerning technology in general.

The results of our cluster analysis support that the relationship of university students to technology and AI is multidimensional and cannot be treated in a homogeneous way. The relationship to AI often differs from the general openness to technology, which also confirms the validity and meaning of using our own TRI AI questionnaire. Targeted communication and education strategies can be assigned to different clusters, which take into account individual receptivity and differences in assessment and utility.

Moderate correlations between the TRI AI and the original TRI scales support the argument that AI-specific attitudes and views partly derive from general attitudes toward technology but also require an independent, specialized approach. The typology consisting of four clusters allows the targeted development of students and the fine-tuning of the curricula.

Data availability statement

The data were collected at the Budapest University of Technology and Economics (BME) in 2025. Derived data supporting the findings of the study are available upon request.

Ethics statement

The research involving human participants, including the use of personal data, was conducted in accordance with the ethical principles set out in the Helsinki Declaration. The study protocol was reviewed and approved in accordance with the Code of Ethics of the Budapest University of Technology and Economics (BME Code of Ethics, 2023), which regulates research ethics at the institution. The approval for the research was obtained through the institutional supervision mechanisms specified in the Code.

Limitations

Based on the sampling, the conclusions of the research can be applied only to BME students participating in engineering training.

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