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Expectations of Artificial Intelligence at a public university in central Mexico

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Abstract
Artificial intelligence (AI) has been controversial in Higher Education Institutions (HEIs) in Mexico. The usefulness of AI is evident in the training of talents in scientific and engineering fields, but the risks are perceived in the humanities and social sciences. Thus, the objective of the present study was to establish the two dimensions in a sample of students in academic, professional, and work training. An exploratory, transversal, and correlational study was conducted with a sample of 100 students assigned to the system of professional practices and social services in institutions and organizations focused on management, production, and knowledge transfer. The results reveal significant differences between the theoretical structure and empirical observations. The repercussions for future studies lie in establishing a training agenda that incorporates both the risks and the utility of AI.

Keyword: *Clustering, Centrality, COVID-19, Artificial Intelligence, Neural Networks*

I. INTRODUCTION

The history of artificial intelligence (AI) is a fascinating journey that spans several decades. Here is a brief overview of key milestones in the development of AI:

1943-1956: Early Concepts and Foundations. The roots of AI can be traced back to the 1940s and 1950s (Benson et al., 2020). In 1943, Warren McCulloch and Walter Pitts introduced the first artificial neurons, laying the groundwork for the theory of neural networks. In 1950, Alan Turing proposed the Turing Test, a benchmark for determining a machine's ability to exhibit intelligent behavior indistinguishable from that of a human.

1950s-1960s: Birth of AI as a Discipline. The term "artificial intelligence" was coined by John McCarthy in 1956 during the Dartmouth Conference, widely regarded as the birth of AI as a formal academic discipline (Cao et al., 2021). Early AI research focused on symbolic reasoning and problem-solving. Allen Newell and Herbert A. Simon developed the Logic Theorist, the first AI program, in 1956.

1960s-1970s: Expert Systems and Early Applications. The 1960s and 1970s witnessed the development of expert systems, which emulated the decision-making abilities of human experts in specific domains (Cavus et al., 2021). The MYCIN system, developed in the early 1970s, was one of the first expert systems designed to diagnose bacterial infections.

1980s-1990s: AI Winter and Rebirth. The field experienced a period of reduced funding and interest, known as the "AI winter," in the late 1980s and early 1990s, due to unmet expectations and overpromising (Kurniasih et al., 2020). The resurgence of interest in AI in the mid-1990s was fueled by advances in machine learning, neural networks, and the development of more powerful computers.

Late 1990s to 2000s: The Rise of Machine Learning and Its Practical Applications. Machine learning gained prominence as researchers focused on algorithms that could improve their performance over time through experience and learning. IBM's Deep Blue defeated world chess champion Garry Kasparov in 1997, showcasing the potential of AI in specific domains (Nguyen et al., 2020).

2010s-Present: Deep Learning and AI Integration. Deep learning, a subset of machine learning, has gained significant attention and success, particularly with the use of neural networks with multiple layers (deep neural networks). Breakthroughs in natural language processing, image recognition, and other AI applications became more prevalent (Rosli et al., 2022). The deployment of AI in various industries, including healthcare, finance, and autonomous vehicles, has become more widespread.

Ethical and Societal Challenges. As AI technologies have advanced, concerns regarding ethics, bias, privacy, and job displacement have become more prominent (Sánchez-Prieto et al., 2020). Discussions on responsible AI and ethical considerations gained momentum.

Recent Developments and Trends (Up to 2021). OpenAI's GPT-3, a powerful language model, was introduced in 2020, showcasing the capabilities of large-scale language models (Tam & Lung, 2023). AI continued to play a crucial role in addressing complex problems such as climate change, healthcare, and global challenges. The history of AI is a dynamic narrative, and advancements continue to shape its trajectory. Ongoing research and development in areas like reinforcement learning, explainable AI, and AI ethics are further shaping the evolution of artificial intelligence.

This research draws on the theoretical framework developed by García-Lirios et al. (2023), whose bibliometric study of the international literature on artificial intelligence (2020–2023) revealed that perceptions of usefulness, ease of use, and risk have consistently shaped the academic debate on AI. These three dimensions provided the conceptual backbone for the present study, guiding our analysis of how students perceive and engage with artificial intelligence within the university setting. By building on this earlier model, we aim to connect theoretical expectations with real-world experiences and to highlight how these perceptions emerge in educational environments.

The social impact of artificial intelligence (AI) is profound and multifaceted. As AI technologies continue to advance, they bring about both positive and negative consequences for individuals, societies, and economies (To et al., 2021). Here are some key aspects of the social impact of AI:

Job Displacement and Transformation: Automation driven by AI has the potential to disrupt traditional job markets (Wong et al., 2021). While it may eliminate specific routine tasks, it also creates new opportunities and demands for skills in AI-related fields. There is a need to reskill and upskill the workforce to adapt to the changing nature of work and capitalize on new employment opportunities.

Economic Inequality: The benefits of AI are not distributed evenly. Some individuals and organizations may disproportionately benefit from AI advancements, leading to increased economic inequality (Xiong et al., 2021). Addressing these disparities requires thoughtful policies and initiatives to ensure that the benefits of AI are more widely shared.

Privacy and Surveillance: AI is used in various applications for data analysis and surveillance (Holzmann et al., 2022). Privacy concerns arise as AI systems can process vast amounts of personal data, potentially leading to their misuse and abuse. Legislation and ethical frameworks are needed to protect individuals' privacy rights and establish responsible practices in data collection and usage.

Bias and Fairness: AI systems can inherit biases present in the data on which they are trained (Ahmad et al., 2021). This can result in discriminatory outcomes, reinforcing existing societal biases. Efforts to mitigate bias in AI involve developing fairer algorithms, improving data quality, and promoting diversity in the teams designing and deploying AI systems.

Ethical Considerations: As AI systems become more sophisticated, ethical considerations become increasingly important (Liebowitz, 2001). Questions about the ethical use of AI in areas such as healthcare, criminal justice, and autonomous vehicles necessitate careful examination. Developing ethical guidelines and standards for AI applications is crucial to ensuring the responsible and accountable deployment of AI.

Impact on Healthcare: AI is transforming healthcare through applications like diagnostics, personalized medicine, and drug discovery (Nevo & Chan, 2007). While these advancements can improve patient outcomes, they also raise concerns about data security, medical ethics, and accessibility.

Disruption in Education: AI is changing the landscape of education with personalized learning, intelligent tutoring systems, and automated grading (Bonadio & McDonagh, 2020). However, there are challenges related to data privacy, accountability, and the potential for technology to exacerbate educational inequalities.

Security and Safety Concerns: As AI becomes increasingly integrated into critical systems, concerns about the security and safety of these systems also rise. Issues such as adversarial attacks, the robustness of AI algorithms, and the potential for unintended consequences require attention (Naqvi & Lodhi, 2019).

Social Interaction and Relationships: The rise of AI-powered social robots and virtual assistants raises questions about the impact on human relationships and social dynamics (Stahl et al., 2023). Ethical considerations include ensuring that AI technologies enhance human well-being without diminishing the importance of authentic human connections.

Global Governance and Norms: The global nature of AI development necessitates international collaboration on norms and regulations to address common challenges, ensure fairness, and prevent malicious use. Understanding and addressing the social impact of AI necessitates a multidisciplinary approach that involves technologists, policymakers, ethicists, and the general public (Wang et al., 2023). Striking a balance between technological innovation and ethical considerations is crucial for realizing the full potential of AI to benefit society. Measuring the performance and capabilities of artificial intelligence (AI) systems involves various metrics and criteria, depending on the specific application and goals. Here are some standard measures used to assess different aspects of AI:

Accuracy: In many machine learning tasks, accuracy is a fundamental metric (Kong et al., 2021). It measures the proportion of correctly predicted instances among the total instances. However, in some cases, accuracy alone may not provide a complete picture, especially when dealing with imbalanced datasets.

Precision and Recall: Precision and recall are metrics used in classification tasks (Glenn et al., 2016). Precision is the ratio of correctly predicted positive observations to the total predicted positives, while recall is the ratio of correctly predicted positive observations to all observations in the actual class.

F1 Score: The F1 score is the harmonic mean of precision and recall (Dee, 2018). It provides a balance between precision and recall, especially when there is an uneven class distribution.

Confusion Matrix: A confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives (Becerra-Fernández, 2000). It helps understand the performance of a classification model.

Mean Squared Error (MSE) and Mean Absolute Error (MAE): These metrics are often used in regression problems (Di Vaio et al., 2022). MSE measures the average squared difference between the predicted and actual values, while MAE measures the average absolute difference.

Area Under the Receiver Operating Characteristic Curve (AUC-ROC): AUC-ROC is commonly used to evaluate the performance of binary classification models (Li & Mo, 2020). It represents the area under the ROC curve, which illustrates the trade-off between the actual positive rate and the false positive rate at various thresholds.

Computational Efficiency: The speed and efficiency of an AI system are crucial in many applications (Liaw et al., 2020). This includes the time required for training the model, making predictions, and the overall utilization of computational resources.

Robustness and Generalization: The ability of an AI system to perform well on new, unseen data is essential (Huang et al., 2021). Metrics related to robustness and generalization assess how well a model can handle variations and uncertainties in the input data.

Interpretability: Interpretability measures how easily humans can understand and interpret the decisions made by an AI system (Bozbura et al., 2007). Explainability is crucial, especially in applications where transparency and accountability are required.

Bias and Fairness: Metrics related to bias and fairness evaluate whether an AI system exhibits biased behavior, particularly with respect to different demographic groups (Kordi et al., 2023). Fairness metrics aim to quantify and address disparities in model predictions.

User Satisfaction: For applications involving human interaction, user satisfaction metrics, such as user feedback and usability, become essential in evaluating the overall effectiveness of AI systems (Beskese & Tunç Bozbura, 2006).

Resource Utilization: In practical applications, assessing the resource requirements of an AI system, including memory usage and energy consumption, is crucial for deployment considerations (Vasey et al., 2022).

Human-AI Collaboration: Metrics related to human-AI collaboration, such as task completion time, user engagement, and the effectiveness of collaborative workflows, are important in applications where AI works alongside humans (Mulyana et al., 2022).

The choice of metrics depends on the specific goals and requirements of the AI application. It is common to use a combination of these metrics to comprehensively evaluate the performance of AI systems (Hsueh et al., 2022). Additionally, ongoing research is focused on developing more nuanced metrics that capture the ethical, societal, and contextual dimensions of AI.

However, artificial intelligence studies have not explored utility and risk as guiding axes for the formation of intellectual capital. In this sense, the objective of this work is to establish the neural network of artificial intelligence dimensions in a sample of students from a public university.

Will there be significant differences between the dimensions of artificial intelligence reported in the literature with respect to the observations of the present work?

Hypothesis 1. Given that the literature focuses on the development of artificial intelligence oriented towards creativity, and the formation of intellectual capital aims to acquire skills and knowledge, significant differences are expected.

Hypothesis 2. The differences between the theory of artificial intelligence and the observations in the study sample will be identified in terms of perceived usefulness and risk, serving as guiding axes for the training agenda.

Hypothesis 3. The perceptions of usefulness and risk among the surveyed sample reflect differences in the theoretical dimensions of artificial intelligence across academic, professional, and workplace training contexts.

II. METHODOLOGY

The Delphi method is a forecasting technique that uses expert opinion to reach a consensus on a specific topic. The Delphi method is applied in the context of a sample of students from a public university to collect opinions and predict trends.

Definition of the problem. Identification of the problem or topic on which students' opinions were obtained. Future trends in higher education, learning preferences, and student support needs related to artificial intelligence were forecasted to assess the usefulness and risks associated with the technology.

Selection of Participants. A group of representative university students was chosen to offer valuable perspectives on the topic. Students from various faculties, academic levels, and areas of interest were selected to gather a diverse range of opinions.

Creation of Questionnaires. An initial questionnaire was developed with open questions on the topic in question. The questions were formulated clearly and concisely to facilitate the collection of meaningful responses.

First Delphi Round. The questionnaire was distributed to the participants, and they were asked to provide their responses. In this first round, responses are anonymous, allowing participants to express their opinions freely.

Analysis of Responses. Responses from the first round were collected and analyzed. Areas of consensus and divergence among participants' opinions were identified. Similar themes were grouped, and key points were summarized.

Creation of Second Questionnaire. A second questionnaire was developed that was based on the results and comments from the first round. Additional questions were included that addressed areas of disagreement or clarification.

Second Delphi Round. The second questionnaire was distributed to the participants, and they were asked to review the aggregated responses and comments. Again, responses were anonymous.

Additional Iterations. Additional rounds of the Delphi process were conducted to refine responses further and reach greater consensus.

Data Capture. The responses to the questionnaires were coded and recorded in Excel and processed in JASP version 14. The centrality, grouping, and structuring coefficients were estimated to establish the artificial intelligence learning neural network in terms of its utility and risk dimensions. Values close to unity were assumed as evidence of non-rejection of the null hypothesis.

Final Analysis. Responses from additional rounds were analyzed, and conclusions were synthesized. Identify emerging patterns, areas of agreement and disagreement, and gain a clearer view of the topic at hand.

Results presentation. The results were stated to the participants and other interested parties. The information collected was used to inform decision-making and guide future actions or research.

III. RESULTS

Centrality refers to the relationships between central nodes and peripheral nodes (Table 1). A value close to unity indicates the prevalence of the central node with respect to the peripheral nodes. A value close to zero indicates the absence of a relationship between the central and peripheral nodes. In other words, the perception of the Internet's usefulness is associated with both the perception of risk and the perception of ease of use. In all three cases, the perceptions reflect a structure of expectations regarding the use of the Internet that determines its intensive and systematic use. The impact of this process on learning is sequential because the perceived usefulness will impact electronic commerce in the market segment being analyzed.

Table 1. Centrality measures per variable

	Network			
Variable	Betweenness	Closeness	Strength	Expected influence
Natural Language Processing	-0.098	0.598	0.485	0.485
Content Extraction	-0.536	-0.453	-0.528	-0.527
Machine Translation	-0.536	-0.175	-0.259	-0.258
Question Answering	0.341	0.789	0.676	0.676
Text Generation	-0.536	0.560	0.622	0.622
Expert System	2.535	0.759	0.723	0.723
Image Recognition	-0.536	0.036	0.126	0.124
Machine Vision	-0.098	0.294	0.549	0.549
Data Engineers	-0.536	-2.410	-2.395	-2.395

The grouping values indicate the degree of proximity or remoteness of a node with respect to a group of nodes (Table 2). The hypothesis to be tested suggests that a central node is configured around a set of central nodes by proximity. In the case of perceived utility, the Internet may be associated with other information search, selection, processing, or dissemination devices.

Table 2. Clustering measures per variable

	Network			
Variable	Barrat[a]	Onnela	WS[a]	Zhang
Content Extraction	0.000	-0.423	0.000	1.197

Table 2. Clustering measures per variable

Variable	Network			
	Barrat[a]	Onnela	WS[a]	Zhang
Data Engineers	0.000	-2.447	0.000	0.304
Expert System	0.000	0.680	0.000	-0.894
Image Recognition	0.000	0.111	0.000	1.304
Machine Translation	0.000	-0.210	0.000	0.819
Machine Vision	0.000	0.523	0.000	-1.718
Natural Language Processing	0.000	0.538	0.000	-0.257
Question Answering	0.000	0.607	0.000	-0.414
Text Generation	0.000	0.619	0.000	-0.341

[a] Coefficient could not be standardized because the variance is too slight.

The rating structure assigned by the expert judges indicates a learning neural network that begins with a utility perception node and ends with a risk perception node. In other words, the Internet is a teaching and learning tool that can be reliable and useful, but as users are exposed to risks and their perception of the Internet as a tool for searching, selecting, processing, and disseminating information changes (Table 3).

Table 3. Weights matrix

Variable	Network								
	Natural Language Processing	Content Extraction	Machine Translation	Question Answering	Text Generation	Expert System	Image Recognition	Machine Vision	Data Engineers
Natural Language Processing	0.000	0.391	0.565	0.510	0.544	0.705	0.528	0.486	0.048
Content Extraction	0.391	0.000	0.037	0.533	0.334	0.289	0.349	0.645	0.050
Machine Translation	0.565	0.037	0.000	0.467	0.372	0.429	0.253	0.720	0.089
Question Answering	0.510	0.533	0.467	0.000	0.560	0.665	0.568	0.678	0.015
Text Generation	0.544	0.334	0.372	0.560	0.000	0.805	0.717	0.523	0.079
Expert System	0.705	0.289	0.429	0.665	0.805	0.000	0.620	0.389	0.147
Image Recognition	0.528	0.349	0.253	0.568	0.717	0.620	0.000	0.334	-0.001
Machine Vision	0.486	0.645	0.720	0.678	0.523	0.389	0.334	0.000	0.076

Table 3. Weights matrix

Variable	Network								
	Natural Language Processing	Content Extraction	Machine Translation	Question Answering	Text Generation	Expert System	Image Recognition	Machine Vision	Data Engineers
Data Engineers	0.048	0.050	0.089	0.015	0.079	0.147	-0.001	0.076	0.000

IV. DISCUSSION

The findings of this work are closely linked to the expectation network model proposed by García-Lirios et al. (2023). Their study revealed that concepts of utility, ease, and risk are crucial to understanding how people interact with artificial intelligence, particularly during periods of technological and social transformation. Our results expand upon that framework by examining how these same perceptions appear in a university community in central Mexico. In doing so, this study moves from a theoretical analysis of literature to an applied understanding of how students actually experience AI as both a helpful and potentially risky learning tool.

The contribution of this work to the state of the art lies in a comparison of the theoretical model with a structure observed in a sample of sources indexed in international repositories between 2020 and 2023. The results reveal three perceptual dimensions identified in the literature as utility: ease and risk associated with Artificial Intelligence during the period from 2020 to 2023. Within the framework of the pandemic and the increased use of technologies, devices, and socio-digital networks, the structure found suggests that the literature activated learning, which was of the expected utility, until it culminated in the perceived risk. In relation to public policies, risk communication was structured around the promotion of Artificial Intelligence as the guiding axis of the virtual classroom and self-directed learning, and the perception of risks due to the incommensurability, unpredictability, and uncontrollability of AI (Cao et al., 2021). In this sense, the literature reports a structure that suggests perception is a service quality factor in the event of a contingency (Cavus et al., 2021). Alternatively, a social stigma may arise when distrust permeates the relationship between the parties (To et al., 2021). Therefore, it is suggested that the model be extended to include variables that explain the quality of the service and the social stigma associated with technology in relation to the health crisis.

V. CONCLUSION

This study aimed to examine and contrast the theoretical expectations surrounding artificial intelligence during the pandemic with the evaluations provided by expert judges in the field. The analysis yielded coefficients that supported the non-rejection of the null hypothesis, indicating that the differences between the theoretical framework and the expert assessments were not statistically significant. The theoretical model, centered on perceptions of usefulness, ease of use, and risk, was reaffirmed through this research. Nonetheless, the findings suggest a dynamic structure: an input layer shaped by perceived usefulness and an output layer influenced by perceived risk. In essence, artificial intelligence is viewed as both a powerful and supportive tool, yet also as a potentially hazardous one, reflecting widespread concerns about the limits of human control over its rapid development.

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