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Modeling AI Automation Potential in Knowledge-Intensive Media Work

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Abstract

Previous studies of artificial intelligence (AI)-driven automation have mostly assessed entire occupations, providing limited evidence about differences among individual tasks. This study addresses this limitation by proposing an NLP-assisted task-level assessment framework for estimating the automation potential of journalistic work. Of the 30 task descriptions listed for the O*NET occupation "News Analysts, Reporters, and Journalists" (27-3023.00), 25 were retained following scope-based screening and grouped into ten composite tasks representing the focal news-production workflow. Each task was assessed across three dimensions—Verb Type, Social Dependence, and Skill Type—using NLP-assisted feature extraction and structured consensus-based evaluation. The resulting component scores were combined into a composite automation potential score ranging from 0 to 1. Editing visual content and filing stories obtained the highest estimated scores (0.97), followed by gathering background information and collecting media content (0.77). Arranging interviews (0.20), conducting interviews (0.23), and receiving assignments to develop story ideas (0.27) received the lowest estimated scores. The study contributes a transparent and interpretable proof-of-concept approach for operationalizing task-level automation potential across procedural, social, and skill-related dimensions. The resulting scores represent relative task-level estimates rather than observed rates or probabilities of workplace automation. With larger labeled task datasets, the three dimensions defined in this framework could provide a basis for supervised classification and subsequent predictive modeling of automation potential across broader task collections.

Keywords: artificial intelligence; automation potential; journalism; natural language processing; task-level analysis; human–AI collaboration

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1. Introduction

Automation has a rich history, from textile machines during the Industrial Revolution to contemporary robotic automation, but more recent advancements in digital automation, such as artificial intelligence (AI), machine learning, natural language processing (NLP), and computer vision, have increased the number of tasks that computers can accomplish [1–3]. This has enabled machines to undertake not only physically demanding tasks but also cognitively demanding tasks that were previously considered unique to humanss [4]. The need for the interpretation of the implications that automation has on labor, particularly concerning mentally demanding domains such as journalism, is thus a critical topic [5].

Among the most frequently cited research articles on the effects of forthcoming computerization on human labor, Ref. [6] estimated the vulnerability of different occupations to computerization using a Gaussian process classifier, suggesting that nearly 47% of total

U.S. employment is at risk of automation within the next decade or two. This forecast has been viewed with great alarm, perceiving automation basically as an occupational threat to job sustainability. After that, later research has revealed that although computerization is significantly altering labor markets, it is not a threat that substitutes entire occupations but modifies the composition of tasks within a job [7]. More recent studies, thus, highlight that automation should be examined at the task level rather than the occupation level, as different tasks within the same occupation present different levels of automation potential [7].

Building on this approach, the authors of [8] argued that the automation-risk debate has failed to account for the potential use of technologies that support, rather than substitute human work. They showed an appreciation of how particular tasks are changing, especially in expanding industries. The results of their analysis demonstrated that tasks emphasizing interpersonal skills, high-level cognitive skills, and system-level thinking are more resilient to automation. This supports a shift from a deterministic perspective on technological unemployment to a more dynamic perspective on occupational change, with a particular emphasis on the development of job types that combine human and machine skills.

A notable sector that includes high-tech transformation is the journalistic profession. In particular, with the latest advancements in AI, journalists now use AI-assisted software not only for routine tasks such as retrieving dataset information, but also for more cognitively intensive tasks such as preparing content, structuring stories, and even automated visual storytelling [5]. From story-template-driven algorithms to the use of large language models such as ChatGPT, the modern journalistic workflow now includes the use of AI systems that continue to shape the definition of what constitutes a typical journalistic task. Nonetheless, even with this shift, most existing literature on the risks of automation has been based on occupational-level analyses, which tend to obscure the fine-grained nature of automation risk at the task level [6,9,10]. The journalistic profession, with tasks that are a diverse intersection of investigative, creative, and communicative tasks, is thus an ideal context for studying automation on a per-task level. This research investigates automation on a per-task level through a computational approach that defines automatability based on linguistic and cognitive factors and focuses on the following research question: Which journalistic tasks tend to have higher or lower estimated automation potential? and the sub questions:

RQ1: Which journalistic tasks show relatively higher or lower estimated automation potential based on Verb Type, Social Dependence, and Skill Type?
RQ2: What is the distribution of automation risks at different stages of the journalistic process?
RQ3: How can NLP techniques be used to analyze and estimate the automatability of tasks?

To answer these questions, we bring together data from the U.S. Department of Labor's O*NET database, a database that provides descriptions on a task level, as well as a skill level, on a broad range of occupations. O*NET is essentially a standardized occupational classification system that provides detailed information on skill requirements, abilities, and job tasks, broken down on an occupation-by-occupation basis. We examine the newly revised occupational classification 27-3023.00, News Analysts, Reporters, and Journalists, identifying tasks and corresponding skills/abilities. We employ an NLP-assisted task-level assessment approach in which journalistic tasks are evaluated across three dimensions: Verb Type, Social Dependence, and Skill Type. NLP-based entity extraction is used as supporting textual evidence for the assessment of Social Dependence, while the final task classifications and scores are determined through structured consensus-based evaluation.

The current research makes two main contributions. First, it provides a fine-grained task-level analysis of differences in estimated automation potential across the journalistic

production process, moving beyond occupation-level assessments. Second, it proposes a transparent and interpretable proof-of-concept framework that operationalizes automation potential across three dimensions—Verb Type, Social Dependence, and Skill Type—while incorporating NLP-based entity extraction as supporting evidence for social dependence. Importantly, the categorical structure developed in this framework also provides a foundation for constructing larger labeled datasets and subsequently training supervised models to classify previously unseen tasks and estimate their automation potential.

2. Background

The task-based methodology for evaluating the risk of automation has been supported by several researchers. In examining tasks, tasks were divided into routine manual, routine cognitive, and non-routine cognitive tasks [11]. A further distinction by including non-routine analytical and non-routine interactive tasks in addition to those identified in the earlier classification made in [12]. In a similar manner, routineness was identified as an important factor in automatability in [13]. However, AI systems are highly efficient in making probabilistic choices but less so in cases of ambiguity, novelty, and unpredictability [13]. In such situations, human intelligence, particularly metacognition, is essential because algorithms lack context and therefore require human oversight [7].

Building on this task-based perspective, several studies have identified the characteristics that make tasks more or less susceptible to automation. Crowston and Bolici state that stable, routine tasks with a minimal number of exceptions are highly automatable, whereas irregular tasks with a large number of exceptions are difficult to automate [14]. Similarly, Frey and Osborne identify three computerization bottlenecks that constrain automation: perception and manipulation, creative intelligence, and social intelligence [6]. They use O*NET variables to demonstrate that tasks requiring originality, social perceptiveness, persuasion, and fine motor skills are less susceptible to automation. Likewise, Frey et al. identify originality and service orientation as attributes that are particularly resistant to automation because of their association with creativity and interpersonal interaction [15]. Bakhshi et al. reached similar conclusions, showing that creativity, idea fluency, active learning, decision-making, systems analysis, and evaluation are among the skills most resilient to automation [8].

Although these theoretical frameworks provide valuable insights into automation, most were developed before recent advances in generative AI. Generative AI systems such as ChatGPT, DALL·E, and Sora can now support tasks involving writing, visual content generation, and interpretation. For example, Pulari et al. demonstrate the use of prompting and reinforcement learning from human feedback for news summarization [16]. Their study illustrates how recent NLP methods can support a specific task within the news production process. Therefore, previously established assumptions regarding automation resistance require re-evaluation.

Motivated by these developments, this study operationalizes theoretical concepts from the automation literature through three task-level dimensions: Verb Type, Social Dependence, and Skill Type. Verb Type captures differences between interaction-oriented, creative/evaluative, and routine/procedural actions; Social Dependence represents the extent to which task performance relies on interpersonal interaction or organizational coordination; and Skill Type captures interpersonal/social, creative/higher-order cognitive, and technical/operational requirements. NLP-based entity extraction is used as supporting textual evidence for assessing Social Dependence by identifying human, organizational, and contextual information in task descriptions. The O*NET database provides standardized task descriptions and skill information that enable these theoretical dimensions to be operationalized at the task level.

However, the application of these frameworks to journalism remains limited. Journalistic work can be considered a knowledge-intensive process because it requires workers to gather and evaluate information and make context-dependent decisions. Seidel et al. similarly emphasize that knowledge-intensive processes are flexible, difficult to estimate, and shaped by the informed decisions of knowledge workers [17]. Existing research on automated journalism [18–21] has primarily focused on automated news reporting. The broader editorial workflow also includes research, verification, interviews, editing, and distribution. These activities involve different levels of procedural, social, and cognitive complexity. By integrating theories of automation with NLP-assisted task-level assessment, this study proposes a fine-grained framework for assessing automation potential across the journalistic workflow. Table 1 summarizes the related work reviewed for this study.

Table 1. Summary of the literature review.

Study	Main Focus or Contribution	Main Advantage	Limitation	Relevance to the Present Study
Autor et al. (2020) [11]	Classifies tasks as routine manual, routine cognitive, and non-routine cognitive	Moves automation analysis from occupations to task characteristics	Uses broad task categories that may not capture differences within complex workflows	Provides the basic task-level perspective
Spitz-Oener (2006) [12]	Distinguishes non-routine analytical and non-routine interactive tasks	Provides a more detailed classification of non-routine work	Does not provide a computational method for scoring individual tasks	Supports the distinction between cognitive and interactive journalistic tasks
Jarrahi (2018) [13]	Examines human–AI collaboration in decision-making	Recognizes the importance of ambiguity, novelty, and human metacognition	Provides a conceptual perspective rather than measurable automation scores	Supports the inclusion of cognitive complexity and human oversight
Ocal and Crowston (2024) [7]	Examines the importance of context and human oversight in algorithmic work	Highlights limitations arising from the lack of contextual understanding	Does not provide an occupational-scale measurement framework	Supports the treatment of contextual dependence as an automation constraint
Crowston and Bolici (2019) [14]	Relates routineness, stability, and exceptions to automation potential	Provides clear task characteristics associated with automatability	Depends primarily on conceptual task assessment	Supports the use of linguistic task descriptions to identify routineness
Frey and Osborne (2017) [6]	Identifies perception and manipulation, creativity, and social intelligence as automation bottlenecks	Uses O*NET variables to estimate automation susceptibility	Produces occupation-level rather than individual task-level estimates	Provides theoretical variables for evaluating automation resistance
Frey et al. (2016) [15]	Identifies originality and service orientation as resistant to automation	Emphasizes creative and interpersonal task characteristics	Predates recent generative AI capabilities	Supports the evaluation of creativity and social interaction
Bakhshi et al. (2017) [8]	Identifies skills such as creativity, active learning, decision-making, and systems analysis as resilient	Extends automation analysis to future skill requirements	Relies on expert-coded occupational information	Supports the use of O*NET skill complexity indicators

Table 1. *Cont.*

Study	Main Focus or Contribution	Main Advantage	Limitation	Relevance to the Present Study
Pulari et al. (2025) [16]	Uses prompting and improved RLHF for news summarization	Demonstrates a recent NLP application within news production and incorporates human feedback	Focuses on one news-production task rather than the full journalistic workflow	Provides evidence that recent generative AI methods can support specific journalistic tasks
Hinderks et al. (2024) [22]	Uses a tertiary study to identify requirements across people/social, technology/artifacts, and process/practice dimensions	Provides a structured and multidimensional synthesis of technological practices	Examines user experience management rather than occupational automation or journalism	Supports consideration of human, technological, and process-related dimensions
Seidel et al. (2023) [17]	Develops model-based decision support for knowledge-intensive processes	Accounts for flexible and context-dependent decisions made by knowledge workers	Supports decisions but does not estimate the automation potential of individual tasks	Supports the characterization of journalism as flexible and knowledge-intensive work
Carlson (2015, 2018) [18,19]	Examines automated journalism and its implications for journalistic authority and practice	Provides a sociotechnical understanding of automated journalism	Focuses mainly on automated news production and its consequences	Establishes the journalism-specific context
Dörr (2016) [21]	Examines the use of algorithms in automated journalism	Provides a systematic account of automated news production	Does not compare automation potential across the entire workflow	Shows how structured news production can be automated
Caswell and Dörr (2018) [20]	Examines automated journalism as a process of computational news production	Connects automated content generation with journalistic practice	Concentrates primarily on news generation	Demonstrates the need to examine tasks beyond automated reporting
Present study	Develops an NLP-assisted task-level framework based on Verb Type, Social Dependence, and Skill Type, with entity extraction supporting the assessment of Social Dependence	Provides a transparent and interpretable proof-of-concept framework for comparing automation potential across individual tasks	Estimates automation potential from standardized task descriptions rather than direct observations of workplace automation	Extends automation analysis across the broader journalistic workflow and provides a foundation for future data-driven task-level automation prediction

3. Materials and Methods

To examine the automation potential of journalistic work at the task level, this study combines structured occupational information from O*NET, NLP-assisted feature extraction, and structured consensus-based assessment across Verb Type, Social Dependence, and Skill Type.

3.1. Task Identification and Mapping

We used O*NET categories for job analysis pertaining to automation potential in the journalism field, specifically job category 27-3023.00: News Analysts, Reporters, and Journalists. Following a scope-based screening, 25 task descriptions were retained and grouped into 10 composite tasks representing the focal end-to-end process of preparing a news item. Five tasks (#2, #10, #23, #27, and #29) were excluded because they primarily represented

broadcast presentation or anchoring, audience-facing communication, or supervisory work rather than the production of an individual news item. The retained task descriptions were grouped according to functional similarity, temporal position in the news-production process and interdependence. Each of the 25 retained task descriptions was assigned once to the composite task that most directly represented its primary function. The complete set of 30 original task descriptions, including their study task numbers, inclusion/exclusion status, and composite-task mappings, is provided in Appendix A Table A1.

Figure 1 illustrates the workflow represented by the ten composite journalistic tasks identified in this study. The task labels correspond directly to the composite-task names reported in Table 2.

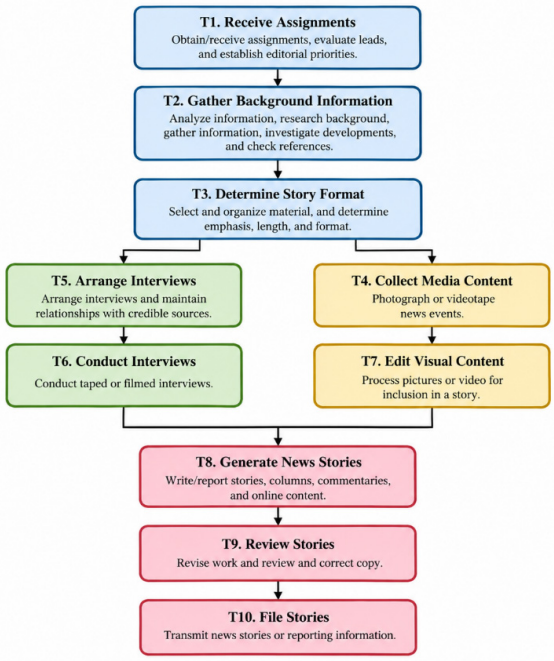


Figure 1. Workflow Diagram of the Ten Composite Journalistic Tasks (T1–T10).

Table 2. Mapping of O*NET tasks.

Composite Task	Mapped O*NET Tasks	Sample O*NET Descriptions
T1. Receive Assignments	#3, #5, #21	Obtain/receive assignments; evaluate leads; establish editorial priorities
T2. Gather Background Information	#4, #6, #8, #14, #15, #20	Analyze information; research background; gather information; investigate developments; check references
T3. Determine Story Format	#9, #18	Select and organize material; determine emphasis, length, and format
T4. Collect Media Content	#22	Photograph or videotape news events
T5. Arrange Interviews	#7, #11	Arrange interviews; maintain relationships with credible sources
T6. Conduct Interviews	#25	Conduct taped or filmed interviews
T7. Edit Visual Content	#24	Process pictures or video for inclusion in a story
T8. Generate News Stories	#1, #12, #17, #26, #28, #30	Write/report stories, columns, commentaries, and online content
T9. Review Stories	#13, #16	Revise work; review and correct copy
T10. File Stories	#19	Transmit news stories or reporting information

The workflow begins with T1. Receive Assignments, where journalists receive editorial assignments, screen leads, and establish story priorities or directions. This composite task incorporates O*NET tasks #3, #5, and #21.

This is followed by T2. Gather Background Information, which includes analyzing information, researching story backgrounds, gathering information from different sources, reviewing notes, investigating developments, and checking reference materials. This composite task incorporates O*NET tasks #4, #6, #8, #14, #15, and #20.

The following step is T3. Determine Story Format, where reporters determine the emphasis, organizational structure, length, and format of a story. This corresponds to O*NET tasks #9 and #18 and represents a decision point in the workflow.

From this stage, the workflow branches into two related information-acquisition activities: T4. Collect Media Content (O*NET #22), involving the collection of photographic or video material from news events, and T5. Arrange Interviews (O*NET #7 and #11), involving the arrangement of interviews and the maintenance of relationships with credible information sources. These activities feed into T6. Conduct Interviews (O*NET #25), which represents the actual conduct of taped or filmed interviews or narratives, and T7. Edit Visual Content (O*NET #24), which involves processing pictures or video for inclusion in a story. After the information-gathering process, T8. Generate News Stories incorporates tasks #1, #12, #17, #26, #28, and #30, covering the writing and reporting of news stories, columns, commentaries and online content. Drafts then undergo T9. Review Stories (#13 and #16), which includes revision and editorial correction. Finally, T10. File Stories (#19) represents the transmission of completed news stories or reporting information for subsequent publication or broadcast.

3.2. Task-Level Feature Assessment

For each of the ten composite tasks, the assessment focused on three complementary dimensions of automation potential: verb type, social dependence and skill type. These dimensions were selected based on the task-automation literature reviewed in the Background section. Verb type captures the nature of the action expressed in the task description, social dependence captures the extent to which task performance depends on interaction or coordination with other people or organizations, and skill type captures the principal cognitive, interpersonal, or technical capabilities required to perform the task. Together, these dimensions represent distinct but complementary procedural, social, and skill-related characteristics relevant to task-level automation potential.

The assessment combined NLP-assisted feature extraction with structured human evaluation. Named Entity Recognition (NER) was used as one source of textual evidence for assessing social dependence rather than as a direct measure of social interaction. The final classifications were determined through structured consensus among the research team consisting of the author and two master's-level journalism students.

Verb Type Categorization: The principal action verb(s) in each task description were examined and classified as routine/procedural, creative/evaluative, or interaction-oriented. Routine/procedural actions represent relatively structured and repeatable operations. Creative/evaluative actions involve content development, interpretation, judgment, or evaluation. Interaction-oriented actions involve communication, coordination, or engagement with other people. This categorization was informed by prior research linking routineness, creativity, and human interaction to differences in automation susceptibility [6,14].

Social Dependence and NLP-Based Entity Extraction: Social dependence was operationalized using NLP-based entity extraction from the retained O*NET task descriptions. The procedure used spaCy's en_core_web_lg model (spaCy version 3.8.16; Python 3.13.5), supplemented with a domain-specific PhraseMatcher to capture journalism-related rela-

tional and contextual expressions that may not be identified by a general-purpose NER model. PERSON-, ORG-, and LOC-related information extracted from the task descriptions was used to characterize human, organizational and contextual dependencies relevant to automation. The outputs are reported in Appendix B Table A2.

The purpose of the entity-extraction stage was not to evaluate NER performance as an independent prediction task, but to computationally extract task characteristics relevant to automation potential. Because entity presence alone does not fully represent the relational requirements of a task, the extracted information was considered together with explicit interaction-related cues in the task descriptions.

Skill Type Categorization: Relevant O*NET skill and ability descriptors were examined in relation to the functional requirements of each composite task and classified into three broad categories: interpersonal/social, creative/higher-order cognitive, and technical/operational/structured information-processing. Interpersonal/social skills include capabilities such as social perceptiveness, persuasion, and active listening. Creative/higher-order cognitive skills include originality, critical thinking, judgment, and related capabilities. Technical/operational/structured information-processing skills include comparatively structured activities involving information organization, monitoring, processing, or quality control. This categorization was informed by prior automation research [6,8].

The task-level classifications were reviewed and finalized through structured consensus. This procedure was used to ensure consistent interpretation of the task descriptions in the present proof-of-concept analysis.

3.3. Scoring Automation Potential

Following the task-level categorization described in Section 3.2, each composite task was assigned an automation potential score for each of the three dimensions: Verb Type, Social Dependence, and Skill Type. Each dimension was first classified into one of three predefined categories representing different levels of automation susceptibility. Rather than assigning a single fixed numerical value to each category, each category was associated with a predefined score range on a 0–1 scale. The exact score within the corresponding range was then assigned according to the relative strength of the task characteristic, based on structured consensus among the research team.

Table 3 presents the operational scoring rubric constructed by the research team and used to convert these task-level classifications into numerical automation potential scores. For each dimension, the assigned category defined the corresponding score range, while the exact value within that range reflected the degree to which the characteristic was present in the task.

Table 3. Operational rubric for task-level automation potential scoring.

Dimension	Category	Operational Definition	Automation Potential Score Range
Verb Type	Interaction-Oriented	Actions inherently involving direct communication, coordination, interviewing, or interpersonal engagement	0.00–0.29
	Creative/Evaluative	Actions involving interpretation, evaluation, judgment, selection, or content development	0.30–0.69
	Routine/Procedural	Structured, repeatable, or procedurally defined actions that can more readily be represented computationally	0.70–1.00

Table 3. *Cont.*

Dimension	Category	Operational Definition	Automation Potential Score Range
Social Dependence	High	Successful task performance substantially depends on interpersonal interaction, relationships, coordination, or human engagement	0.00–0.39
	Moderate	Task performance involves some interpersonal or organizational dependence, but such interaction is not the dominant requirement	0.40–0.69
	Low	Task can largely be performed without direct interpersonal or relational dependence	0.70–1.00
Skill Type	Interpersonal/Social	Predominantly requires interpersonal capabilities such as active listening, social perceptiveness, persuasion, or relationship management	0.00–0.39
	Creative/Higher-order Cognitive	Predominantly requires judgment, interpretation, originality, critical thinking, or other higher-order cognitive capabilities	0.20–0.69
	Technical/Operational/Structured Information-processing	Predominantly involves structured information processing, technical operations, monitoring, organization, or quality-control activities	0.70–1.00

Note: Higher scores indicate greater estimated automation potential. The score ranges represent operational bounds for the task-level assessment. Within each category, the exact score reflects the assessed strength of the corresponding task characteristic. The ranges for Interpersonal/Social and Creative/Higher-order Cognitive skill types partially overlap because these categories represent qualitatively different types of human capability rather than successive levels of automation potential.

The three component scores were subsequently combined to calculate an overall automation potential score for each composite task. Equal weighting was adopted as a transparent baseline because no empirical evidence was available to justify assigning greater importance to any one of the three dimensions. The composite automation potential score for task i was therefore calculated as:

$$A_i = \frac{V_i + D_i + S_i}{3} \quad (1)$$

where A_i represents the composite automation potential score for task i, V_i represents the Verb Type automation score, D_i represents the Social Dependence automation score, and S_i represents the Skill Type automation score. Each component score ranges from 0 to 1 according to the rubric presented in Table 3, and the resulting composite score therefore also ranges from 0 to 1. Higher values indicate greater estimated automation potential.

For descriptive interpretation, the resulting composite scores were grouped into three levels of automation potential: low (0.00–0.39), moderate (0.40–0.74), and high (0.75–1.00). These thresholds were established as heuristic interpretive cutoffs within the structured consensus-based scoring framework and were applied consistently across all composite tasks. They are intended to facilitate relative comparison among tasks in this proof-of-concept assessment and should not be interpreted as empirically validated boundaries of automation.

4. Findings

The ten composite journalistic tasks were assessed across the three dimensions of the proposed framework: Verb Type, Social Dependence, and Skill Type. The following sections present the results for each dimension, followed by the composite automation potential scores obtained by combining the three component scores.

4.1. Verb Type

The Verb Type analysis classified the dominant actions associated with each composite task as interaction-oriented, creative/evaluative, or routine/procedural, following the rubric presented in Table 3. Interaction-oriented actions received lower automation potential scores because their execution depends more strongly on direct human communication or engagement. Creative/evaluative actions received low-to-moderate scores depending on the degree of interpretation, judgment, or content development involved, whereas routine/procedural actions received higher scores because they were comparatively structured and operational.

As shown in Table 4, Receive Assignments (T1), Arrange Interviews (T5), and Conduct Interviews (T6) were characterized primarily as interaction-oriented and each received a Verb Type score of 0.20. Determine Story Format (T3) and Generate News Stories (T8) were classified as creative/evaluative and received scores of 0.30, while Review Stories (T9) also fell within the creative/evaluative category but received a slightly higher score of 0.40, reflecting its comparatively more structured evaluative character. In contrast, Gather Background Information (T2), Collect Media Content (T4), Edit Visual Content (T7), and File Stories (T10) were characterized predominantly as routine/procedural and received scores of 1.00. These results illustrate the range-based scoring procedure: tasks within the same broad category were not necessarily required to receive identical scores, as the exact value reflected the relative strength of the task characteristic within the corresponding rubric range based on the research team's consensus.

Table 4. Verb Type classification and automation potential scores.

	Task	Verb Type	Rubric Range	Automation Score
T1	Receive Assignments	Interaction-Oriented	0.00–0.29	0.20
T2	Gather Background Information	Routine/Procedural	0.70–1.00	1.00
T3	Determine Story Format	Creative/Evaluative	0.30–0.69	0.30
T4	Collect Media Content	Routine/Procedural	0.70–1.00	1.00
T5	Arrange Interviews	Interaction-Oriented	0.00–0.29	0.20
T6	Conduct Interviews	Interaction-Oriented	0.00–0.29	0.20
T7	Edit Visual Content	Routine/Procedural	0.70–1.00	1.00
T8	Generate News Stories	Creative/Evaluative	0.30–0.69	0.30
T9	Review Stories	Creative/Evaluative	0.30–0.69	0.40
T10	File Stories	Routine/Procedural	0.70–1.00	1.00

4.2. Social Dependence

The Social Dependence analysis assessed the extent to which successful performance of each composite task depended on interpersonal interaction, organizational coordination, or relationship-based engagement. NLP-based entity extraction was used to identify PERSON-, ORG-, and LOC-related information in the task descriptions, together with explicit relational cues relevant to the nature of the task. Following the rubric in Table 3, tasks were classified as having high, moderate or low social dependence. Tasks with higher social dependence received lower automation potential scores for this dimension, whereas tasks with lower social dependence received higher scores.

As depicted in Table 5, Arrange Interviews (T5) and Conduct Interviews (T6) showed high social dependence and received scores of 0.20, reflecting their strong reliance on direct interpersonal engagement. Receive Assignments (T1) also showed high social dependence but received a slightly higher score of 0.30. Gather Background Information (T2) and Collect Media Content (T4) were assessed as moderately socially dependent and received scores of 0.50. In contrast, Determine Story Format (T3), Edit Visual Content (T7), Generate News Stories (T8), and File Stories (T10) showed low social dependence and received scores of 1.00, while Review Stories (T9) received a score of 0.90 within the same category.

Table 5. Social Dependence Classification and Automation Potential Scores.

Task	NER Result	Social Dependence	Rubric Range	Automation Score
T1	PERSON, ORG	High	0.00–0.39	0.30
T2	ORG, LOC	Moderate	0.40–0.69	0.50
T3	None	Low	0.70–1.00	1.00
T4	ORG, LOC	Moderate	0.40–0.69	0.50
T5	PERSON	High	0.00–0.39	0.20
T6	PERSON	High	0.00–0.39	0.20
T7	None	Low	0.70–1.00	1.00
T8	None	Low	0.70–1.00	1.00
T9	None	Low	0.70–1.00	0.90
T10	None	Low	0.70–1.00	1.00

Importantly, the Social Dependence classification was not determined solely by the presence or absence of extracted named entities. Explicit relational requirements expressed in the task descriptions were also considered. For example, Review Stories (T9) was classified as having low social dependence because its core activities are largely performed independently; however, the requirement to revise work introduces a limited degree of interpersonal dependence. It therefore received a score of 0.90 rather than 1.00 within the low-social-dependence range.

4.3. Skill Type

The Skill Type analysis examined the dominant capabilities required to perform each composite task. Following the rubric presented in Table 3, these requirements were classified as interpersonal/social, creative/higher-order cognitive, or technical/operational/structured information-processing. Tasks relying more strongly on interpersonal or higher-order cognitive capabilities received lower automation potential scores for this dimension, whereas tasks characterized predominantly by structured technical or operational requirements received higher scores.

As illustrated in Table 6, Receive Assignments (T1) and Conduct Interviews (T6) received Skill Type scores of 0.30, while Arrange Interviews (T5) received a score of 0.20, reflecting their substantial interpersonal/social requirements. Determine Story Format (T3) received a score of 0.20, Generate News Stories (T8) received 0.30, and Review Stories (T9) received 0.40, reflecting differences in the degree and nature of creative, evaluative, and higher-order cognitive requirements across these tasks. In contrast, Gather Background Information (T2) and Collect Media Content (T4) received scores of 0.80, while Edit Visual Content (T7) and File Stories (T10) received scores of 0.90, reflecting their comparatively stronger technical, operational, or structured information-processing characteristics.

Table 6. Skill Type Classification and Automation Potential Scores.

Task	Existing Skills/Abilities	Skill Type Category	Rubric Range	Automation Score
T1	Social perceptiveness, decision making	Interpersonal/Social	0.00–0.39	0.30
T2	Reading comprehension, information ordering	Technical/Operational	0.70–1.00	0.80
T3	Originality, decision making	Creative/Higher-order Cognitive	0.20–0.69	0.20
T4	Operation monitoring, visualization	Technical/Operational	0.70–1.00	0.80
T5	Persuasion, social perceptiveness	Interpersonal/Social	0.00–0.39	0.20
T6	Active listening, oral expression	Interpersonal/Social	0.00–0.39	0.30
T7	Quality control, visual color discrimination	Technical/Operational	0.70–1.00	0.90
T8	Originality, fluency of ideas	Creative/Higher-order Cognitive	0.20–0.69	0.30
T9	Problem sensitivity, critical thinking	Creative/Higher-order Cognitive	0.20–0.69	0.40
T10	Written expression, information organization	Technical/Operational	0.70–1.00	0.90

4.4. Composite Automation Scores

In order to assess the overall automation potential of each reporting activity, a composite automation score was calculated as described in Section 3.3. This composite indicator takes into consideration Verb Type, Social Dependence, and Skill Type. The automation potential score ranges from 0.00 (lowest estimated automation potential) to 1.00 (highest estimated automation potential). The composite scores are displayed in Table 7 together with the descriptive automation potential categories (Low, Moderate, and High).

Table 7. Composite automation scores with categories.

Task ID	Task Description	Verb Type	Social Dependence	Skill Type	Automation Score	Automation Category
T1	Receive assignments	0.20	0.30	0.30	0.27	Low
T2	Gather background info	1.00	0.50	0.80	0.77	High
T3	Determine story format	0.30	1.00	0.20	0.50	Moderate
T4	Collect media content	1.00	0.50	0.80	0.77	High
T5	Arrange interviews	0.20	0.20	0.20	0.20	Low
T6	Conduct interviews	0.20	0.20	0.30	0.23	Low
T7	Edit visual content	1.00	1.00	0.90	0.97	High
T8	Generate news stories	0.30	1.00	0.30	0.53	Moderate
T9	Review stories	0.40	0.90	0.40	0.57	Moderate
T10	File stories	1.00	1.00	0.90	0.97	High

Having established the composite scores, we proceed to discuss our findings within the context of our research questions.

4.5. Answers to Research Questions

The main research question of this study was: Which journalistic tasks tend to have higher or lower estimated automation potential? Overall, the findings show that the estimated automation potential of journalistic tasks varies according to their procedural, social, and skill-related characteristics. Editing visual content and filing stories received the highest composite scores (0.97), followed by gathering background information and collecting media content (0.77). In contrast, arranging interviews (0.20), conducting interviews (0.23), and receiving assignments to develop story ideas (0.27) received the lowest scores. Verb Type, Social Dependence, and Skill Type jointly distinguished tasks involving structured

and procedural actions from those requiring interpersonal interaction, contextual judgment, and complex cognitive skills.

RQ1: Which journalistic tasks show relatively higher or lower estimated automation potential based on Verb Type, Social Dependence, and Skill Type?

Our task-level analysis shows varying automation potential across the ten core journalistic tasks identified in this study. By combining Verb Type, Social Dependence, and Skill Type, we obtained a composite automation potential score for each task (see Table 7 and Figure 2). Tasks such as T2 (Gather Background Information), T4 (Collect Media Content), T7 (Edit Visual Content), and T10 (File Stories) were classified as having high estimated automation potential, with composite scores exceeding 0.75. In contrast, T1 (Receive Assignments), T5 (Arrange Interviews), and T6 (Conduct Interviews) received scores below 0.30 and were classified as having low estimated automation potential. T3 (Determine Story Format), T8 (Generate News Stories), and T9 (Review Stories) fell within the moderate range.

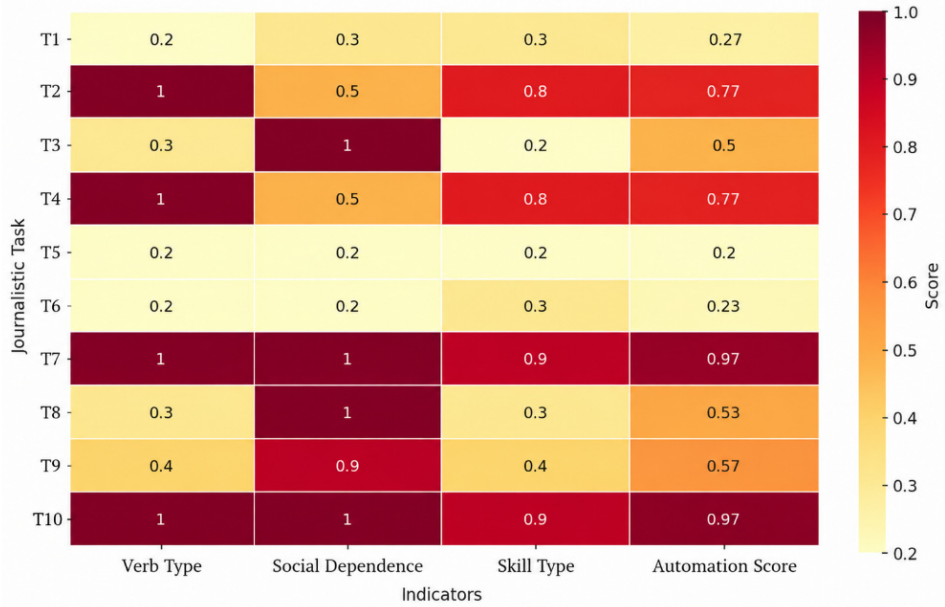


Figure 2. Heatmap of Task-Level Scores Across Verb Type, Social Dependence, and Skill Type.

RQ2: How is estimated automation potential distributed across different stages of the journalistic process?

The ten journalistic tasks can be organized into three functional stages of the news production process. As shown in Figure 2, the estimated automation potential varies both across and within these stages.

Planning and interpersonal stage (T1, T5, and T6): Receiving assignments to develop story ideas (T1), arranging interviews (T5), and conducting interviews (T6) received low composite automation scores of 0.27, 0.20, and 0.23, respectively. These task descriptions involve interpersonal communication, coordination, and context-dependent interaction. Their low scores are therefore consistent with the importance of social and cognitive skills in this stage.

Information-gathering and production-preparation stage (T2, T3, T4, and T7): Gathering background information (T2) and collecting media content (T4) both received high scores of 0.77, while editing visual content (T7) received a score of 0.97. These tasks contain comparatively structured actions related to retrieval, acquisition, and editing. However, determining the story format (T3) received a moderate score of 0.50, indicating that not all tasks within this stage have the same automation potential.

Content production, review, and distribution stage (T8, T9, and T10): Generating news stories (T8) and reviewing stories (T9) received moderate scores of 0.53 and 0.57, respectively. These results indicate the potential for AI support while also reflecting the linguistic and skill complexity associated with narrative construction and editorial review. In contrast, filing stories (T10) received a high score of 0.97, consistent with its more structured and procedural characteristics.

Overall, the distribution is not linear across the journalistic workflow. Tasks do not become progressively more or less automatable as the workflow advances. Instead, their estimated automation potential varies according to the characteristics of each task. Interpersonal tasks generally received low scores, structured information-processing tasks received higher scores, and content-generation and editorial tasks occupied a moderate position.

RQ3: How can NLP techniques be used to analyze and estimate the automatability of tasks?

This study demonstrates how NLP-assisted feature extraction can be integrated with structured task-level assessment to estimate relative automation potential. In the present proof-of-concept, journalistic tasks are assessed across three dimensions—Verb Type, Social Dependence and Skill Type—each of which is represented by three predefined categories. Verb Type distinguishes interaction-oriented, creative/evaluative, and routine/procedural tasks; Social Dependence distinguishes high, moderate, and low dependence; and Skill Type distinguishes interpersonal/social, creative/higher-order cognitive, and technical/operational/structured information-processing requirements. NLP-based entity extraction additionally supports the assessment of Social Dependence by identifying human, organizational, and contextual information in task descriptions.

An important contribution of the proposed framework is that these categorical dimensions provide a basis for developing a future supervised task-level automation prediction pipeline. With sufficiently large labeled datasets, separate text-classification models could be trained to predict Verb Type, Social Dependence, and Skill Type from previously unseen task descriptions. Transformer-based models such as BERT or RoBERTa, for example, could be fine-tuned as three separate classifiers, each distinguishing among the three categories defined for the corresponding dimension. For the Social Dependence classifier, NLP-based entity extraction could also support the construction and annotation of the training dataset by identifying PERSON-, ORG-, and LOC-related information and other relational cues associated with interpersonal or organizational dependence. These entity-extraction outputs would serve as supporting information for assigning Social Dependence labels rather than as automation scores themselves.

The outputs of these classifiers could subsequently be incorporated into a broader automation-score prediction model. For example, the predicted categories could be represented through dummy or one-hot encoded variables and used as predictors in a linear regression model trained against an independently defined automation score. Verb Type, Social Dependence, and Skill Type would constitute an initial set of task-level predictors rather than a comprehensive set; additional task characteristics could be incorporated as larger datasets. Once trained and validated, such a pipeline could receive a previously unseen task description, classify it across the relevant task characteristics, and use these predicted features to estimate an automation score. Linear regression represents one interpretable example, while alternative supervised regression models could also be evaluated depending on the available data.

The present study does not train these classification or regression models. Rather, it provides a proof-of-concept framework that defines and operationalizes an initial set of task-level characteristics and demonstrates how NLP-assisted information can contribute to their assessment. The framework therefore provides a foundation for constructing larger

labeled datasets and subsequently developing and empirically validating a more fully data-driven automation-prediction system across occupations and workplace settings.

5. Discussion

The emergence of AI applications in knowledge-intensive fields has triggered changes in professional practices, and the media are no exception [23,24]. For many decades, journalists have been applying a variety of technologies, from typewriters, cameras, and computers to smartphones and tablets, in order to collect, produce, and disseminate information [25]. In recent years, new genres such as podcasts, data graphics, and interactive storytelling in virtual or augmented reality have expanded the repertoire of presentation formats [21]. Now, the use of AI application software, especially natural language generation software, inducts a new era in this process [4]. The immediacy and scalability that these technologies add to the handling of very large quantities of data are prone to characteristic problems of transparency, verification, privacy, bias, and accountability [26,27]. Thus, far from making professional journalists unnecessary, automation seems to increase the importance of uniquely human capacities such as judgment, curiosity, and skepticism in order to keep the produced information accurate, contextual, and useful within society. In this context, our research proposed a framework to examine how different elements of journalistic tasks are differentially susceptible to automation.

5.1. Task-Level Comparison of the Findings with Prior and Recent Literature

Our framework assigned T1 (Receive Assignment) a low estimated automation potential score (0.27), representing that this task relies heavily on direct communication with editors, situation awareness, and decision-making. This finding is consistent with the work of Frey and Osborne [6], which identifies socially intensive tasks as highly resistant to automation. Similarly, Schapals and Porlezza [28] suggest that editorial briefing remains a fundamentally human activity that cannot be replaced by AI. Recent evidence also highlights the importance of editorial accountability in maintaining human oversight of assignment decisions [29], further supporting our findings.

T2 (Gather Background Information) was identified with a high estimated automation potential score (0.77). This finding is consistent with current newsroom practices. Publications such as Bloomberg and the Los Angeles Times employ AI-assisted systems to analyze, process, and organize real-time information [30]. Beckett [31] reported that nearly half of surveyed journalists use AI for story suggestion, trend detection, and event monitoring. More recently, the Reuters Institute [29] reported that AI-assisted background research has become common in many newsrooms, supporting the high automation potential identified by our framework.

Our results indicate that T3 (Determine Story Format) has a moderate estimated automation potential score (0.50). Although AI systems can assist in suggesting story structures and generating draft outlines, determining the narrative focus, framing, and editorial perspective remains dependent on human judgment. This observation is consistent with [8], who argue that creativity-related tasks are inherently more resistant to automation, and with [7], who emphasize the continuing importance of human editorial judgment.

According to our framework, T4 (Collect Media Content) received a high estimated automation potential score (0.77). This finding is consistent with existing AI applications in journalism. Systems such as InVID [32] and Vox Civitas [33] have been used to support the retrieval, filtering, and organization of multimedia content. More broadly, advances in multimodal AI have expanded computational capabilities for processing and organizing visual and other media content. These developments are consistent with the relatively high automation potential estimated for this task within the proposed framework.

Our framework assigns T5 (Arrange Interviews) a low estimated automation potential score (0.20). Although AI can assist in identifying sources and supporting scheduling activities, arranging interviews requires persuasion, trust building, and interpersonal communication. Frey and Osborne [6] similarly identify social intelligence as a major barrier to automation. Schapals and Porlezza [28] suggest that AI may support organizational aspects of interview scheduling, whereas establishing trust with sources remains a fundamentally human activity. These findings are also consistent with recent ethical discussions on AI-assisted journalism [26].

The results indicate that T6 (Conduct Interviews) has low automation potential (automation score = 0.23). Although chatbot-assisted interviews have been explored [34,35], these systems remain limited in adaptive communication, contextual understanding, and interpersonal interaction. Consequently, interviewing continues to be regarded as mostly human-centered activity, which supports the low automation score assigned by our framework. This result should not be interpreted as suggesting that AI cannot support interview preparation. LLMs can assist journalists in generating, refining, and organizing interview questions. However, the composite task examined here concerns the conduct of the interview itself, which additionally involves real-time interaction, adaptive follow-up, interpretation of verbal and contextual cues, rapport and trust, and the interviewee's willingness to engage with an AI-mediated interaction. In this respect, resistance to automation may arise not from an AI system's inability to formulate questions, but from the social and relational conditions under which those questions are asked. This distinction helps explain the low estimated automation potential score assigned to T6 within the proposed framework.

Our framework assigns T7 (Edit Visual Content) one of the highest estimated automation potential scores (0.97). Previous studies have shown that photo and video editing tasks—including validation, tagging, summarization, and cropping—can be effectively supported by AI systems [36,37]. Recent advances in multimodal large language models have further enabled automated caption generation and visual content enhancement, which is consistent with the high automation potential identified in our analysis.

Our framework assigns T8 (Generate News Stories) a moderate automation potential score (0.53). Previous studies have demonstrated that automated news generation is particularly effective for highly structured domains such as financial reports, sports news, crime statistics, and traffic updates [38]. At the same time, the moderate score obtained in the present analysis reflects the creative and higher-order cognitive requirements associated with narrative development, critical reasoning, originality, and contextual judgment. Recent examples, such as Il Foglio's AI-generated newspaper [39], further illustrate the limitations of current generative AI regarding factual accuracy and editorial judgment.

According to our framework, T9 (Review Stories) received a moderate estimated automation potential score (0.57). Routine editing activities, including grammar correction and formatting, can be supported by AI-based writing assistants. However, editorial review involving fact-checking, ethics, and contextual evaluation continues to require human oversight [38]. Recent Reuters Institute reports (2024–2025) also highlight that AI hallucinations remain a significant challenge, supporting our finding that editorial review is only partially automatable.

Our framework assigns T10 (File Stories) one of the highest estimated automation potential scores (0.97). Content management systems, search engine optimization tools, and automated publishing platforms already support much of this workflow. This task profile is consistent with the increasing use of digital systems to support content transmission and publishing workflows [29]. As with the other scores, the value of 0.97 represents a relative estimate derived from the proposed framework and should not be interpreted as an observed automation rate.

5.2. Generative AI and the Limits of Substitution

The emergence of generative models such as ChatGPT, Claude, and Gemini has fueled discussions on the future of creative work [40], including that of journalists [5,7]. The capabilities of these models to compose coherent and stylistically similar text have expanded the range of journalistic tasks that can potentially be supported by AI, particularly in news writing, although our analysis indicates considerable variation in automation potential across tasks.

Tasks such as 'gather background information' and 'edit visual content' received relatively high automation potential scores because they involve comparatively structured and procedural characteristics. For instance, tasks such as "arranging interviews" or "evaluating stories" are highly dependent on tacit knowledge, ethics, and audience awareness, which are skills that even the most advanced LLMs lack. This is supported by the empirical assessment that indicates AI-created content might be on a similar level to human-created content in terms of grammar, coherence, but lacks when it comes to uniqueness and factualness [26,41,42].

Consequently, rather than replacing journalistic work, generative AI can be described as a partner that can help with particular tasks such as draft preparation, summarization, and media retrieval, while retaining the essential human aspects within these tasks.

5.3. Methodological Contribution: An NLP-Assisted Task-Level Assessment Approach

The methodological contribution of this study is a transparent task-level framework for operationalizing multiple dimensions of automation potential rather than a fully automated NLP prediction model. The framework evaluates tasks across three interpretable dimensions—Verb Type, Social Dependence, and Skill Type—each represented by three predefined categories. NLP-based entity extraction is incorporated as a supporting computational component for assessing Social Dependence by identifying human, organizational, and contextual information in task descriptions. The framework therefore makes the assumptions underlying task-level automation assessment explicit and enables procedural, social, and skill-related characteristics to be considered within a common and interpretable scoring structure.

A further contribution is the framework's potential to serve as a foundation for more data-driven task-level automation assessment. The categorical structure developed in this study provides clearly defined targets that can subsequently be operationalized using supervised learning as larger labeled datasets become available. As discussed in RQ3, this structure could support the development of automated classification and prediction models for previously unseen task descriptions. Importantly, the three dimensions introduced here should be regarded as an initial set of task-level characteristics rather than a representation of the determinants of automation potential.

The present study should therefore be understood as a proof-of-concept that establishes an operational and interpretable structure for task-level automation assessment. Its contribution lies not in demonstrating a fully automated prediction system, but in providing a framework that can subsequently be expanded, computationally implemented, and empirically validated using larger task collections and independently observed automation outcomes.

5.4. Practical Implications for Newsrooms, Educators, and Policymakers

From a newsroom perspective, the findings suggest that AI-assisted automation may be particularly applicable to comparatively structured tasks involving information gathering, media processing, and content transmission, while tasks involving interviewing and interpersonal interaction may require greater human involvement. This creates opportuni-

ties for the development of "hybrid newswork" that combines human capabilities with AI technologies [31,43].

For journalism education, the implications are associated with the need to revise the curriculum so that it includes AI literacy, data reasoning, prompt writing, and design thinking lectures. Journalism skills that students should acquire not only involve the ability to write but also the capacity to operate automated systems.

Policymakers can use the research results to support a responsible automation approach that involves transparency, interpretation, and equity in journalism. Journalistic values—truth, accountability, and fairness—should be preserved by AI technologies while the potential erosion of journalistic process credibility should be addressed [28,44].

5.5. Role Shifts in Journalism Practice

Prior research on automation in the field of journalism was mostly concentrated on the question of whether journalists would be replaced due to automation [45–47]. However, in more recent literature, the question of how the roles of journalists change due to the application of AI becomes more common.

The research of Schapals and Porlezza [28] explored the influence of AI technologies on journalists via the analysis of semi-structured interviews in German newsrooms. The study revealed that in most cases, journalists consider AI technologies as being complementary rather than substitutes. In particular, journalists perceive the creative process of writing and editorial control as processes highly resistant to automation.

The same conclusion was reached in the research of Bucher [45] in relation to Swedish newsrooms, where it was demonstrated that computer-based solutions increase rather than substitute human agency. Furthermore, in [48], it was found that despite the possibility of automation of routine activities, journalists still conduct interpretation, investigation, and contextualization of information. Such conclusions match with the results of our research, according to which procedural tasks are more automatable than creative and interpersonal ones.

5.6. Emergence of Hybrid Roles

As AI technologies become increasingly integrated into news production, journalistic work may involve more hybrid combinations of editorial, technological, and data-related responsibilities. Rather than necessarily creating entirely new occupational roles, this development may require journalists and other newsroom professionals to work more closely with automated systems and technical specialists. Diakopoulos [38] identified the growing importance of algorithmic accountability, highlighting the need for journalists to develop competencies related to programming, data, and computational systems. The increasing use of AI may therefore contribute to changes in the skill sets required in contemporary journalism.

5.7. Reframing Automation as Augmentation

One of the theoretical contributions of this research is that it supports the developing paradigm of Augmented Journalism [5,42]. Rather than suggesting uniform substitution of journalistic work by AI, the task-level results indicate differing opportunities for human–AI collaboration across journalistic activities. Tasks characterized by structured and procedural requirements showed higher estimated automation potential, whereas tasks involving interpersonal interaction and higher-order judgment showed lower estimated potential. This pattern is consistent with user-centered research [13,14], which has identified assistive uses of applications such as ChatGPT in journalism, including support for developing story angles.

5.8. Limitations and Future Research Directions

This research proposes a framework to estimate automation potential at the task level by focusing on journalism. Journalism is used as a case study for demonstrating the framework and is not intended to represent all forms of journalistic work across countries and organizational settings. The analysis is based on the O*NET occupation "News Analysts, Reporters, and Journalists" and therefore reflects standardized task descriptions developed within the U.S. occupational context. Future research could apply the proposed framework to larger task collections, different occupations, media organizations, and task descriptions from other national contexts to examine its generalizability.

The present study should also be understood as a proof-of-concept based on a relatively small set of composite tasks and structured consensus-based assessment. The classifications and within-category scores were determined through the assessment procedure described in the methodology rather than through a large-scale expert elicitation process or independently observed workplace outcomes. Future studies could therefore involve larger and more diverse expert panels and employ formal expert-elicitation approaches, such as Delphi, to further evaluate the classification and weighting of task characteristics.

With continued advances in AI capabilities, the automation potential of individual tasks may also evolve. Accordingly, the proposed framework should be viewed as a dynamic approach that can be updated as AI technologies and professional practices change. The current framework also evaluates tasks separately and does not capture situations in which one professional performs multiple interdependent tasks or roles. Future studies could aggregate task-level estimates according to task frequency or the proportion of working time allocated to different activities.

NLP-based entity extraction was used as supporting information for assessing Social Dependence; however, the present study does not constitute a formal evaluation of NER performance. Future research could compare alternative NLP models using larger and more diverse task collections and examine whether entity-based and other linguistic features improve the classification of Social Dependence.

The present study uses equal weights for Verb Type, Social Dependence, and Skill Type to maintain transparency and avoid introducing unsupported assumptions about their relative importance. These weights were not empirically optimized, and alternative weighting schemes could affect the resulting composite scores. Future research could therefore conduct sensitivity analyses and compare equal weighting with expert-derived or empirically estimated weighting schemes.

Finally, the automation potential scores reported in this study are relative estimates derived from task descriptions rather than measurements of observed workplace automation. Future research should validate the framework against independent evidence, such as observed AI adoption, or other task-level automation outcomes. Larger labeled datasets could also enable the development of the supervised classification and prediction models.

6. Conclusions

This study proposes an NLP-assisted task-level framework for estimating automation potential in journalism across three dimensions: Verb Type, Social Dependence, and Skill Type. The findings indicate higher estimated automation potential for comparatively procedural tasks, such as filing stories, and lower estimated potential for tasks involving considerable interpersonal interaction, such as conducting interviews. The study provides a proof-of-concept framework for task-level automation assessment that can serve as a foundation for future data-driven approaches using larger labeled datasets and additional task characteristics. Future research could extend the framework across occupations, national contexts, and real-world workplace settings.

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Data Availability Statement: The data used in this study were derived from publicly available resources provided by O*NET OnLine. The occupational data for News Analysts, Reporters, and Journalists (ONET-SOC Code 27-3023.00) are available at: https://www.onetonline.org/link/summary/27-3023.00 (accessed on 29 July 2025).

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. O*NET Task Descriptions, Inclusion Decisions, and Composite-Task Mapping.

Study Task No.	Original O*NET Task Description	Status	Composite Task/Exclusion Rationale
#1	Write commentaries, columns, or scripts, using computers.	Included	T8. Generate News Stories
#2	Coordinate and serve as an anchor on news broadcast programs.	Excluded	Broadcast presentation/anchoring; outside the focal news-item production workflow
#3	Examine news items of local, national, and international significance to determine topics to address, or obtain assignments from editorial staff members.	Included	T1. Receive Assignments
#4	Analyze and interpret news and information received from various sources to broadcast the information.	Included	T2. Gather Background Information
#5	Receive assignments or evaluate leads or tips to develop story ideas.	Included	T1. Receive Assignments
#6	Research a story's background information to provide complete and accurate information.	Included	T2. Gather Background Information
#7	Arrange interviews with people who can provide information about a story.	Included	T5. Arrange Interviews
#8	Gather information and develop perspectives about news subjects through research, interviews, observation, and experience.	Included	T2. Gather Background Information
#9	Select material most pertinent to presentation, and organize this material into appropriate formats.	Included	T3. Determine Story Format
#10	Present news stories, and introduce in-depth videotaped segments or live transmissions from on-the-scene reporters.	Excluded	Broadcast presentation; outside the focal production workflow
#11	Establish and maintain relationships with individuals who are credible sources of information.	Included	T5. Arrange Interviews

Table A1. *Cont.*

Study Task No.	Original O*NET Task Description	Status	Composite Task/Exclusion Rationale
#12	Report news stories for publication or broadcast, describing the background and details of events.	Included	T8. Generate News Stories
#13	Revise work to meet editorial approval or to fit time or space requirements.	Included	T9. Review Stories
#14	Review and evaluate notes taken about news events to isolate pertinent facts and details.	Included	T2. Gather Background Information
#15	Investigate breaking news developments, such as disasters, crimes, or human-interest stories.	Included	T2. Gather Background Information
#16	Review written, audio, or video copy, and correct errors in content, grammar, or punctuation, following prescribed editorial style and formatting guidelines.	Included	T9. Review Stories
#17	Report on specialized fields such as medicine, green technology, environmental issues, science, politics, sports, arts, consumer affairs, business, religion, crime, or education.	Included	T8. Generate News Stories
#18	Determine a published or broadcasted story's emphasis, length, and format, organizing material accordingly.	Included	T3. Determine Story Format
#19	Transmit news stories or reporting information from remote locations, using equipment such as satellite phones, telephones, fax machines, or modems.	Included	T10. File Stories
#20	Check reference materials, such as books, news files, or public records, to obtain relevant facts.	Included	T2. Gather Background Information
#21	Discuss issues with editors to establish priorities or positions.	Included	T1. Receive Assignments—editorial prioritization and story direction
#22	Photograph or videotape news events.	Included	T4. Collect Media Content
#23	Present live or recorded commentary via broadcast media.	Excluded	Broadcast presentation rather than production of the news item
#24	Take pictures or video, and process them for inclusion in a story.	Included	T7. Edit Visual Content
#25	Conduct taped or filmed interviews or narratives.	Included	T6. Conduct Interviews
#26	Develop ideas or material for columns or commentaries by analyzing and interpreting news, current issues, or personal experiences.	Included	T8. Generate News Stories

Table A1. *Cont.*

Study Task No.	Original O*NET Task Description	Status	Composite Task/Exclusion Rationale
#27	Communicate with readers, viewers, advertisers, or the general public via mail, email, or telephone.	Excluded	Audience-facing communication rather than news-item production
#28	Write online blog entries that address news developments or offer additional information, opinions, or commentary on news events.	Included	T8. Generate News Stories
#29	Assign stories to other reporters or duties to production staff.	Excluded	Supervisory/managerial assignment rather than individual news-item production
#30	Write columns, editorials, commentaries, or reviews that interpret events or offer opinions.	Included	T8. Generate News Stories

Note: Study Task No. (#1–#30) refers to the sequential numbering of the 30 O*NET task statements in the dataset version used in this study. These numbers are retained throughout the manuscript to facilitate cross-referencing with Table 2. Because the display order of task statements on O*NET Online may vary across database versions, the corresponding O*NET Task ID is also provided as an identifier. Of the 30 original task descriptions, 25 were retained and mapped to ten composite tasks representing the focal news-production workflow. Five tasks (#2, #10, #23, #27, and #29) were excluded because they primarily concerned broadcast presentation/anchoring, audience-facing communication, or supervisory assignment rather than the production of an individual news item.

Appendix B

Table A2. Task-Level NLP Entity Extraction and Composite-Level Coding.

Composite Task	Study Task No.	Exact O*NET Task Description	Raw NLP Output	Composite-Level NER Result
T1 Receive Assignments	3	Examine news items of local, national, and international significance to determine topics to address, or obtain assignments from editorial staff members.	news items [ORG]; local [LOC]; national [LOC]; international [LOC]; editorial staff members [PERSON]	PERSON, ORG
	5	Receive assignments or evaluate leads or tips to develop story ideas.	None	
	21	Discuss issues with editors to establish priorities or positions.	editors [PERSON]	
T2 Gather Background Information	4	Analyze and interpret news and information received from various sources to broadcast the information.	sources [PERSON]; broadcast [ORG]	ORG, LOC
	6	Research a story's background information to provide complete and accurate information.	None	
	8	Gather information and develop perspectives about news subjects through research, interviews, observation, and experience.	None	
	14	Review and evaluate notes taken about news events to isolate pertinent facts and details.	None	

Table A2. *Cont.*

Composite Task	Study Task No.	Exact O*NET Task Description	Raw NLP Output	Composite-Level NER Result
	15	Investigate breaking news developments, such as disasters, crimes, or human-interest stories.	news developments [ORG]	
	20	Check reference materials, such as books, news files, or public records, to obtain relevant facts.	news files [ORG]; public records [ORG]	
T3 Determine Story Format	9	Select material most pertinent to presentation, and organize this material into appropriate formats.	None	None
	18	Determine a published or broadcasted story's emphasis, length, and format, organizing material accordingly.	None	
T4 Collect Media Content	22	Photograph or videotape news events.	Photograph [PERSON]	ORG, LOC
T5 Arrange Interviews	7	Arrange interviews with people who can provide information about a story.	people [PERSON]	PERSON
	11	Establish and maintain relationships with individuals who are credible sources of information.	individuals [PERSON]; sources [PERSON]	
T6 Conduct Interviews	25	Conduct taped or filmed interviews or narratives.	None	PERSON
T7 Edit Visual Content	24	Process pictures or video for inclusion in a story.	None	None
T8 Generate News Stories	1	Write commentaries, columns, or scripts, using computers.	None	None
	12	Report news stories for publication or broadcast, describing the background and details of events.	news stories [ORG]; publication [ORG]; broadcast [ORG]	
	17	Report on specialized fields such as medicine, green technology, environmental issues, science, politics, sports, arts, consumer affairs, business, religion, crime, or education.	None	
	26	Develop ideas or material for columns or commentaries by analyzing and interpreting news, current issues, or personal experiences.	None	
	28	Write online blog entries that address news developments or offer additional information, opinions, or commentary on news events.	news developments [ORG]	
	30	Write columns, editorials, commentaries, or reviews that interpret events or offer opinions.	None	

Table A2. *Cont.*

Composite Task	Study Task No.	Exact O*NET Task Description	Raw NLP Output	Composite-Level NER Result
T9 Review Stories	13	Revise work to meet editorial approval or to fit time or space requirements.	None	None
	16	Review written, audio, or video copy, and correct errors in content, grammar, or punctuation, following prescribed editorial style and formatting guidelines.	None	
T10 File Stories	19	Transmit news stories or reporting information from remote locations.	news stories [ORG]; remote locations [LOC]	None

Note: Raw NLP Output reports the entities identified at the individual task-description level by the NLP pipeline. Composite-Level NER Result refers to the entity coding used for the corresponding composite task in the Social Dependence assessment reported in Table 5. It reflects the combined task-level assessment and therefore does not necessarily correspond one-to-one with individual raw entity outputs. NER information was used as supporting evidence for Social Dependence rather than as an automation score itself.

References

1. Dalgali, A.; Crowston, K. Sharing Open Deep Learning Models. In Proceedings of the 52nd Hawaii International Conference on System Sciences, Maui, HI, USA, 8–11 January 2019. [CrossRef]
2. Kruskopf, S.; Lobbas, C.; Meinander, H.; Söderling, K.; Martikainen, M.; Lehner, O. Digital Accounting and the Human Factor: Theory and Practice. *ACRN J. Financ. Risk Perspect.* **2020**, *9*, 78–89. [CrossRef]
3. Öcal, A. Otonom araçlara yönelik duygusal tutumlar: BERT modeli ile duygu analizi. *Gazi Üniversitesi Mühendis. Mimar. Fakültesi Derg.* **2025**, *40*, 2515–2526. [CrossRef]
4. Ocal, A. Framing, Emotions, Salience: The Future of AI as Seen by Redditors. Ph.D. Thesis, Syracuse University, Syracuse, NY, USA, 2023. Available online: https://www.proquest.com/docview/2845416849 (accessed on 19 October 2023).
5. Dalgali, A.; Crowston, K. Algorithmic Journalism and Its Impacts on Work. Computation + Journalism Symposium. 2020. Available online: https://cj2020.northeastern.edu/ (accessed on 20 October 2024).
6. Frey, C.B.; Osborne, M.A. The future of employment: How susceptible are jobs to computerisation? *Technol. Forecast. Soc. Change* **2017**, *114*, 254–280. [CrossRef]
7. Ocal, A.; Crowston, K. Framing and feelings on social media: The futures of work and intelligent machines. *Inf. Technol. People* **2024**, *37*, 2462–2488. [CrossRef]
8. Bakhshi, H.; Downing, J.M.; Osborne, M.A.; Schneider, P. *The Future of Skills: Employment in 2030*; Pearson: London, UK, 2017.
9. Grace, K.; Salvatier, J.; Dafoe, A.; Zhang, B.; Evans, O. Viewpoint: When Will AI Exceed Human Performance? Evidence from AI Experts. *J. Artif. Intell. Res.* **2018**, *62*, 729–754. [CrossRef]
10. Walsh, T. Expert and Non-expert Opinion About Technological Unemployment. *Int. J. Autom. Comput.* **2018**, *15*, 637–642. [CrossRef]
11. Autor, D.; Mindell, D.; Reynolds, E. *MIT Work of the Future Task Force*; Fall 2020 MIT Report; MIT: Cambridge, MA, USA, 2020.
12. Spitz-Oener, A. Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. *J. Labor Econ.* **2006**, *24*, 235–270. [CrossRef]
13. Jarrahi, M.H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Bus. Horiz.* **2018**, *61*, 577–586. [CrossRef]
14. Crowston, K.; Bolici, F. Impacts of Machine Learning on Work. In Proceedings of the 52nd Hawaii International Conference on System Sciences, Maui, HI, USA, 8–11 January 2019. [CrossRef]
15. Frey, C.B.; Osborne, M.A.; Holmes, C. Technology at Work v2.0: The Future Is Not What It Used to Be. 2016. Available online: https://www.oxfordmartin.ox.ac.uk/publications/technology-at-work-v2-0-the-future-is-not-what-it-used-to-be/ (accessed on 30 April 2021).
16. Raj Pulari, S.; Umadevi, M.; Vasudevan, S.K. Improved Fine-Tuned Reinforcement Learning From Human Feedback Using Prompting Methods for News Summarization. *Int. J. Interact. Multimed. Artif. Intell.* **2025**, *9*, 59–67. [CrossRef]
17. Seidel, A.; Haarmann, S.; Weske, M. Model-based decision support for knowledge-intensive processes. *J. Intell. Inf. Syst.* **2023**, *61*, 143–165. [CrossRef]

18. Carlson, M. The Robotic Reporter: Automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digit. J.* **2015**, *3*, 416–431. [CrossRef]
19. Carlson, M. Automating judgment? Algorithmic judgment, news knowledge, and journalistic professionalism. *New Media Soc.* **2018**, *20*, 1755–1772. [CrossRef]
20. Caswell, D.; Dörr, K. Automated Journalism 2.0: Event-driven narratives: From simple descriptions to real stories. *J. Pract.* **2018**, *12*, 477–496. [CrossRef]
21. Dörr, K.N. Mapping the field of Algorithmic Journalism. *Digit. J.* **2016**, *4*, 700–722. [CrossRef]
22. Hinderks, A.; Domínguez Mayo, F.J.; Escalona, M.J.; Thomaschewski, J. Requirements for User Experience Management—A Tertiary Study. *Int. J. Interact. Multimed. Artif. Intell.* **2024**, *8*, 160–167. [CrossRef]
23. Dalgali, A.; Crowston, K. Factors Influencing Approval of Wikipedia Bots. In Proceedings of the 53rd Hawaii International Conference on System Sciences, Maui, HI, USA, 7–10 January 2020; pp. 136–145. [CrossRef]
24. Öcal, A.; Xiao, L.; Park, J. Reasoning in social media: Insights from Reddit 'Change My View' submissions. *Online Inf. Rev.* **2021**, *45*, 1208–1226. [CrossRef]
25. Zelizer, B. Why Journalism Is About More Than Digital Technology. *Digit. J.* **2019**, *7*, 343–350. [CrossRef]
26. Ocal, A. Perceptions of AI Ethics on Social Media. In *2023 IEEE International Symposium on Ethics in Engineering, Science and Technology (ETHICS), West Lafayette, IN, USA, 18–20 May 2023*; IEEE: Piscataway, NJ, USA, 2023. [CrossRef]
27. Ocal, A. Moral Decision-making with Artificial Intelligence. In *2025 IEEE International Symposium on Ethics in Engineering, Science, and Technology (ETHICS), Evanston, IL, USA, 6–8 June 2025*; IEEE: Piscataway, NJ, USA, 2025; p. 1. [CrossRef]
28. Schapals, A.K.; Porlezza, C. Assistance or Resistance? Evaluating the Intersection of Automated Journalism and Journalistic Role Conceptions. *Media Commun.* **2020**, *8*, 16–26. [CrossRef]
29. Reuters Institute for the Study of Journalism. Digital News Report 2025. 2025. Available online: https://reutersinstitute.politics.ox.ac.uk/digital-news-report/2025 (accessed on 29 July 2025).
30. Skillman, B.; Miller, C.; Diakopoulos, N.; Fehr, T. How Newsrooms are Embracing Automation. Presented at the NICAR 2020, New Orleans, LA, USA, 5–8 March 2020.
31. Beckett, C. New Powers, New Responsibilities. A Global Survey of Journalism and Artificial Intelligence. Available online: https://blogs.lse.ac.uk/polis/2019/11/18/new-powers-new-responsibilities/ (accessed on 5 May 2021).
32. Nixon, L.; Apostolidis, E.; Markatopoulou, F.; Patras, I.; Mezaris, V. Multimodal Video Annotation for Retrieval and Discovery of Newsworthy Video in a News Verification Scenario. In *MultiMedia Modeling*; Kompatsiaris, I., Huet, B., Mezaris, V., Gurrin, C., Cheng, W.-H., Vrochidis, S., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2019; Volume 11295, pp. 143–155. [CrossRef]
33. Diakopoulos, N.; Naaman, M.; Kivran-swaine, F. Diamonds in the Rough: Social Media Visual Analytics for Journalistic Inquiry. In *2010 IEEE Symposium on Visual Analytics Science and Technology*; IEEE: Piscataway, NJ, USA, 2010.
34. Gruber, J. A Chatbot That Conducts First-Round Interviews. Presented at the Student Research and Creative Activity Fair. 2020. Available online: https://digitalcommons.unomaha.edu/srcaf/2020/schedule/99 (accessed on 21 September 2020).
35. Sidaoui, K.; Jaakkola, M.; Burton, J. AI feel you: Customer experience assessment via chatbot interviews. *J. Serv. Manag.* **2020**, *31*, 745–766. [CrossRef]
36. Papadopoulou, O.; Giomelakis, D.; Apostolidis, L.; Papadopoulos, S.; Kompatsiaris, Y. Context Aggregation and Analysis: A Tool for User-Generated Video Verification. In *Workshop on Reducing Online Misinformation Exposure*; Association for Computing Machinery: New York, NY, USA, 2019; p. 7.
37. Teyssou, D.; Leung, J.-M.; Apostolidis, E.; Apostolidis, K.; Papadopoulos, S.; Zampoglou, M.; Papadopoulou, O.; Mezaris, V. The InVID Plug-in: Web Video Verification on the Browser. In *Proceedings of the First International Workshop on Multimedia Verification, MuVer '17, Mountain View, CA, USA, 27 October 2017*; Association for Computing Machinery: New York, NY, USA, 2017; pp. 23–30. [CrossRef]
38. Diakopoulos, N. Algorithmic Accountability: Journalistic investigation of computational power structures. *Digit. J.* **2015**, *3*, 398–415. [CrossRef]
39. Balmer, C. Italian Newspaper Gives Free Rein to AI, Admires Its Irony. Reuters. Available online: https://www.reuters.com/technology/artificial-intelligence/italian-newspaper-gives-free-rein-ai-admires-its-irony-2025-04-18/ (accessed on 29 July 2025).
40. Ocal, A. Cinematic Narratives as Socio-Technical Systems: Emotion Mining and Script–Audience Emotional Fidelity. *Systems* **2025**, *13*, 994. [CrossRef]
41. Love, H.A.; Adamson, G.; James, M.; Lajoie, J.; Mareels, I.; Pearl, Z.; Schiff, D.S.; Schmitt, K.; Arohi, T.; Buchanan, J.; et al. The Future of Work in the Age of Automation: Proceedings of a Workshop on Norbert Wiener's 21st Century Legacy. *IEEE Trans. Technol. Soc.* **2025**, *6*, 430–452. [CrossRef]
42. Ocal, A. Perceptions of the Future of Artificial Intelligence on Social Media: A Topic Modeling and Sentiment Analysis Approach. *IEEE Access* **2024**, *12*, 182386–182409. [CrossRef]

43. Diakopoulos, N. *Automating the News: How Algorithms Are Rewriting the Media*; Harvard University Press: Cambridge, MA, USA, 2019.
44. Thurman, N. Social Media, Surveillance, and News Work: On the apps promising journalists a 'crystal ball'. *Digit. J.* **2018**, *6*, 76–97. [CrossRef]
45. Bucher, T. 'Machines don't have instincts': Articulating the computational in journalism. *New Media Soc.* **2017**, *19*, 918–933. [CrossRef]
46. Lewis, S.C.; Guzman, A.L.; Schmidt, T.R. Automation, Journalism, and Human–Machine Communication: Rethinking Roles and Relationships of Humans and Machines in News. *Digit. Journal.* **2019**, *7*, 409–427. [CrossRef]
47. van Dalen, A. The algorithms behind the headlines: How machine-written news redefines the core skills of human journalists. *J. Pract.* **2012**, *6*, 648–658. [CrossRef]
48. Pashevich, E. Automation of News Production in Norway: Augmenting Newsroom with Artificial Intelligence. Master's Thesis, University of Oslo, Oslo, Norway, 2018.

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