Linking Policy-Oriented Learning to Policy Change in Collaborative Environmental Governance Processes

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Abstract

Collaboration has become an increasingly popular mechanism for environmental governance over the past three decades. The success of collaborative approaches, however, is often premised on the assumption that stakeholders will learn—about the resource issue itself, relevant policy, other stakeholders' values, and more—as they interact with one another, thereby fostering the development of creative, mutually-beneficial management actions that increase resource sustainability. Despite the centrality of this assumption to the promotion of collaboration as a modern environmental governance tool, gaps remain regarding how to best measure learning or determine what factors promote learning, as well as whether learning leads to policy change. This study uses data from two rounds of interviews and a survey of participants in a statewide, multi-level water governance process in Colorado to analyze the relationship between the procedural aspects of a collaborative process, participants' policy-oriented learning, and consequent policy change. The findings indicate that certain institutional features, alongside one's innate preference for collaborative approaches to decisionmaking, predict an individual's level of policy-oriented learning. Additionally, the degree to which an individual learns significantly predicts their perception of the collective policy change arising from the process. These findings help to develop a theory of policy learning in collaborative contexts and inform the creation of policy processes that more successfully mitigate conflict through cooperation.

Prepared for the Western Political Science Association Annual Meeting
Vancouver, British Columbia
April 13-15, 2017

Introduction

Collaboration has become an increasingly popular mechanism for environmental and natural resource governance over the past three decades (Gerlak, Heikkila, and Lubell 2013; Koontz 2016). By requiring diverse stakeholders to interact repeatedly, explore complex issues in depth, and develop mutually-beneficial environmental management actions, collaborative governance processes have the potential to positively impact the environment and increase resource sustainability while also expanding citizen participation in policymaking. By addressing some of the failures of top-down, command-and-control management, collaborative processes may produce solutions that are more feasible, more widely accepted by stakeholders, and easier to implement (Ansell and Gash 2008; Pahl-Wostl et al. 2007; Sabatier et al. 2005).

The "endurance and success" of collaborative approaches, however, is often premised on the assumption that stakeholders will learn as they interact with one another over time (Gerlak and Heikkila 2011, 620). In other words, as stakeholders gain new knowledge and understanding, potentially leading to revisions in their "professional beliefs regarding facts, values or policies," they are better positioned to reach "political consensus on collective action" (Leach et al. 2014, 592). While learning is considered to be an important element in non-collaborative policy processes as well (May 1992), collaborative settings are expected to be particularly conducive to learning (Leach et al. 2014; Weible and Sabatier 2009). Learning, therefore, is frequently discussed as both an outcome of collaborative governance and an important condition for its success (Ansell and Gash 2008; Emerson, Nabatchi, and Balogh 2012; Koontz 2014; Leach et al. 2014; Pahl-Wostl et al. 2008). Yet, due to a lack of evidence on what conditions actually foster learning, as well as uncertainty surrounding metrics to measure learning, “the theories and empirical evidence of how learning emerges in collaborative governance processes are still in their infancy” (Gerlak, Heikkila, and Lubell 2013, 425).

In response to these gaps, this study uses a mixed-method approach to add to the emerging literature on learning in collaborative environmental governance processes (Gerlak and Heikkila 2011; Heikkila and Gerlak 2013; Koontz 2014; Leach et al. 2014). In keeping with the “second generation” of scholarship on collaborative environmental partnerships, which focuses on developing and testing theories about how key variables interact (Koontz 2016), this study tests four hypotheses derived from the Advocacy Coalition Framework (ACF) and collaborative governance literatures concerning *what procedural features increase policy-oriented learning in collaborative processes, and whether policy-oriented learning leads to policy change*. Exploring how the assumptions about learning embedded in a well-tested policy process framework such as the ACF may need to be adapted for collaborative contexts, and then testing these adaptations empirically, explicitly builds theory about learning in collaborative contexts. It also provides the foundation for a method through which to compare learning in collaborative and traditional settings using a comprehensive policy process framework such as the ACF. The insights gleaned from this analysis can inform the creation of policy processes that more successfully mitigate conflict through cooperation among diverse actors.

The Learning Landscape: Who Learns What and How?

Learning is defined in numerous ways across disciplines and contexts. In the realm of public administration, Leach et al. (2014) define learning as “the process by which people develop a more comprehensive and accurate understanding of the science, technology, law, economics, and politics that underlie the decisions they make or the recommendations they advance" (592). Specific to river management scenarios, Pahl-Wostl et al. (2008) focus on how actors come to understand "their interdependence and differences and [learn] to deal with them constructively… [resulting in] increased management capacity" (485). While learning can lead to behavior change, it may also lead to a change in attitudes or values that is not necessarily reflected in behavior (Muro and Jeffrey 2008), making it particularly difficult to detect and measure.

To further complicate this definition, learning is expected to occur at multiple, interacting levels in collaborative processes (Heikkila and Gerlak 2013). For example, individual actors may learn independently by seeking external scientific information on a topic related to the process (e.g. what pollutants are present in a specific watershed and their effects). Actors may also learn alongside others in a collaborative process, perhaps by attending a presentation by an expert at a process meeting and discussing the implications of the information (e.g., a presentation on what attempts have already been made by scientists and the local government to resolve water quality issues in a community). As actors work together to develop trust, come to consensus on a piece of information, or produce a policy output (e.g., a set of new voluntary guidelines on effluent quality for industries in the community), they may be learning in a more "collective" or "social" fashion (Gerlak and Heikkila 2011; Koontz 2014; Pahl-Wostl et al. 2008).

Additionally, actors may learn *about* a variety of things. For example, in collaborative environmental governance processes, actor may learn about the resource or environmental issue in question, the laws and policies relevant to governing the resource, other stakeholders' values and needs, the social and political feasibility of various management actions, and how to more effectively participate in the process (Koontz 2014; Leach et al. 2014). They may also learn things that are "wrong" by taking up incorrect information or assimilating new information in a biased manner, leading to more "entrenched positions, mistaken assumptions, or co-optation" of the views of less powerful actors (Leach et al. 2014, 594). Considering the variety of things that actors may learn about individually and collectively, it is no surprise that defining and studying learning in collaborative policy processes is a difficult task.

In response to this challenge, policy scholars Heikkila and Gerlak (2013) explore *how* learning takes place in collective policy contexts in order to better measure it. They offer "a theoretically grounded approach for policy scholars to define, understand, and measure learning" (Heikkila and Gerlak 2013, 485) that focuses on two key theoretical concepts: learning processes and learning products. *Learning processes* include the acquisition, translation, and dissemination of information by individuals or the collective through mechanisms such as dialogue and deliberation. *Learning products* include cognitive or behavioral (policy/institutional) changes that result from learning processes on the individual or collective levels, such as new beliefs, strategies, plans, or policies. Uncovering the link between learning processes and learning products in a collective context can help scholars understand if and how learning relates to policy change.

Learning in the Advocacy Coalition Framework

The policy process literature contributes a number of additional learning-related concepts that typically focus on the policy changes that arise from learning. One framework in particular, the Advocacy Coalition Framework (ACF), develops the concept of **policy-oriented learning** as a potential driver of policy change. The ACF purports that complex policy processes can be better understood by grouping actors with similar beliefs and coordination patterns into advocacy coalitions. Within a policy subsystem, coalitions compete with one another to create policies that reflect their beliefs before their opponents can do the same (Sabatier and Weible 2007). While involved in a policy process, actors may experience policy-oriented, defined as "relatively enduring alterations of thought or behavioral intentions that result from experience and/or new information and that are concerned with the attainment or revision of policy objectives" (Sabatier and Weible 2007, 123). The concept of policy-oriented learning captures individual learning about key issues and potential solutions, as well as about "political strategies for achieving objectives" (Jenkins-Smith et al. 2014, 198). Although actors may experience policy-oriented learning within their own coalition, potentially causing them to reinforce pre-existing ideas or develop strategies to make their proposed policies more politically viable at the expense of others, the ACF focuses on learning *across* coalitions with different belief systems. Policy change arising from policy-oriented learning is expected to be incremental and gradual, resulting in only minor changes unless it happens "in conjunction with an external or internal shock" (Jenkins-Smith et al. 2014, 203).

The ACF hypothesizes that policy-oriented learning is most likely to occur under certain conditions: 1) when there is an intermediate level of informed conflict between coalitions, wherein coalitions have the technical resources to engage in debate and the major conflict is not between the coalitions' core beliefs; 2) within a forum that is prestigious and dominated by professional norms; 3) when accepted quantitative data exists, as opposed to qualitative, subjective, or no data; and 4) when problems involve natural systems rather than social or political systems (Jenkins-Smith et al. 2014). Yet, there has been mixed empirical evidence in support of these claims, as well as a dearth of research on how policy-oriented learning is linked to policy change (Jenkins-Smith et al. 2014; Leach et al. 2014; Weible, Sabatier, and McQueen

2009). Furthermore, Weible, Sabatier, and McQueen (2009) argue that collaborative contexts may further alter some of the ACF's expectations about learning.

Research Design

As collaboration becomes an increasingly popular strategy in environmental governance processes, understanding *what procedural features increase policy-oriented learning in collaborative processes, and whether policy-oriented leads to policy change* becomes crucial to analyzing the effectiveness of collaborative approaches (Koontz and Thomas 2006). To investigate this research question, this study first outlines four hypotheses about policy-oriented learning and policy change based on the ACF and collaborative governance literatures. It then tests the hypotheses using a mixed-method case study design focused on a statewide, multi-level collaborative water governance process in Colorado, U.S.A.

Hypotheses

In order to consider how the ACF's assumptions about policy-oriented learning and its connection to policy change may differ in collaborative contexts, one must consider four categories of factors that the ACF expects to explain learning: the attributes of the forum, the level of conflict between coalitions, the attributes of the stimuli, and the attributes of actors (Jenkins-Smith et al. 2014). These factors, which underlie the ACF's traditional hypotheses on learning, essentially speak to the mechanisms underlying individual and collective learning processes (Heikkila and Gerlak 2013). Each category of factors will be discussed in the in light of the relevant literature on collaborative governance processes, resulting in hypotheses about how the factors influence learning in collaborative contexts.[1]

Forums: While collaborative policy subsystems are expected to "provide an optimal setting for learning from science and for learning across coalitions," as actors "cooperate, develop trust, and work with scientists in joint fact-finding to develop a shared knowledge base" (Weible and Sabatier 2009, 208), it is important to consider that the procedural features of collaborative forums vary widely. For instance, some collaborative forums require a higher degree of consensus among actors in order to create policy change than others. This feature is expected to incentivize coalitions "to seek compromise and share information with opponents" (Sabatier and Weible 2007, 200). Following from this, a forum that requires a greater degree of consensus among actors may also produce a greater degree of policy-oriented learning:

H1: Policy-oriented learning across belief systems is more likely to occur in collaborative forums that require a high degree of consensus to produce policy change than in forums with weaker consensus rules.

Level of Conflict and Attributes of Actors: The ACF agues that the attributes of individual actors in a policy process (i.e., their beliefs, resources, strategies, networks) as well as the degree of pre-existing conflict among these actors (i.e. intermediate conflict as the most conducive to learning) may influence how learning occurs (Jenkins-Smith et al. 2014). Some actors may simply be more primed to learn when entering the process, potentially because they hold a higher personal preference for consensus-based decisionmaking processes (Leach et al. 2014; Raadgever, Mostert, and Van de Giesen 2012). Others may develop greater confidence in the process and trust in other participants over time as a result of social interactions and the

[1] Hypotheses 1-3 were previously developed by the author as part of a broader exercise in adapting the ACF for use in studying collaborative contexts; they were illustrated using a limited set of interview data from the same collaborative process that will be discussed here (Koebele Under Review).

facilitation of collaboration by strong leaders, thereby fostering their willingness to learn (Gerlak and Heikkila 2011; Heikkila and Gerlak 2013; Leach et al. 2014; Muro and Jeffrey 2008). While it is difficult to alter deeply-seated individual attributes such as one's innate preference for collaboration over other approaches, collaborative processes may foster learning among even those who are resistant by encouraging actors to interact repeatedly in order to reduce conflict and build trust in the process and one another:

H2: Policy-oriented learning across belief systems is more likely to occur in collaborative forums that require repeated face-to-face interactions over time, especially when facilitated by strong leaders, than in forums where actors are not required to participate in such interactions.

Stimuli: The "attributes of the stimuli," defined as "the type of information and experience coalition actors are exposed to" (Jenkins-Smith et al. 2014, 199), may also influence the degree to which actors learn. It has been traditionally assumed that when actors have more uncertain information that can lead to a broader variety of interpretations, they may be less likely to experience policy-oriented learning. In collaborative processes, however, high levels of scientific certainty surrounding an issue may actually impede learning by minimizing space for important deliberation (Leach et al. 2014). Such deliberative space may help diverse stakeholders "develop a shared vision and plan for moving forward" with an issue (Koontz 2014) and reduce assimilation bias in order to produce more innovative ideas (Heikkila and Gerlak 2013). According to Gerlak and Heikkila (2011), learning may also be more likely to occur when a process is decentralized, incorporates diverse sources of knowledge, and promotes experimentation. Thus, policy-oriented learning may be more likely to occur in processes that utilize these mechanisms, including convening diverse actors to work on complex issues that involve both scientific uncertainty and value conflicts, and providing incentives for these actors to seek consensus through deliberation:

H3: Policy-oriented learning across belief systems is more likely to occur in collaborative forums that incorporate diverse information sources and opportunities to openly deliberate on this information.

Finally, as aforementioned, the ACF designates policy-oriented learning as one of four pathways to policy change. While ACF scholarship traditionally associates the "negotiated agreement" pathway to policy change with collaborative processes, actors must often create shared knowledge about the problem at hand, the universe of potential solutions, and the feasibility of a preferred solution in order to reach a negotiated agreement. In other words, unless negotiations are strictly *quid pro quo*, actors must seek potential points of compromise through learning—about the issue at hand, others' values, relevant policy, and more. From this, a fourth hypothesis that connects the concepts of policy-oriented learning and policy change is proposed:

H4: More policy-oriented learning among actors in a collaborative process will lead to a greater degree of policy change.

Case Study: Colorado's Basin Roundtable Process

The four hypotheses described above will be tested using a mixed-method case study design focused on a statewide, multi-level collaborative water governance process in Colorado, U.S.A., referred to here as the "Roundtable process." Over the last half-century, water resource governance, management, and planning has become a popular context for experimentation with collaborative approaches (Koontz 2014; Pahl-Wostl et al. 2008).

Following a catastrophic drought in Colorado in 2002, Colorado's main water governance entity, the Colorado Water Conservation Board (CWCB), began "the most comprehensive analysis of Colorado water ever undertaken" through the Statewide Water Supply Initiative (State of Colorado 2015). In 2005, a formal stakeholder process component was established through the passage of the Colorado Water for the 21st Century Act (HB-1177) to "facilitate discussions on water management issues and encourage locally driven collaborative solutions” (Colorado Water Conservation Board 2016a). The process went on to involve over 300 Colorado citizens through “Basin Roundtables” that represent the state’s eight hydrologic basins and the Denver Metro area. Simultaneously, a 27-member Interbasin Compact Committee (IBCC) was established “to facilitate discussion across Colorado’s river basins and to address statewide water issues” (Colorado Water Conservation Board 2016b).

Although the Roundtables and IBCC had a number of interim goals such as creating needs assessments of various water use sectors within each basin, their most comprehensive task arose in 2013 when Colorado’s governor issued an executive order mandating the creation of Colorado’s first statewide water plan. The Roundtables were tasked with providing data and insight for the statewide plan through “Basin Implementation Plans” (BIPs) that integrated the information they had gathered since their inception with proposed actions that could help meet each basin’s water supply needs. The BIPs, along with broader policy recommendations created by the IBCC, became the centerpiece of Colorado’s Water Plan (CWP). The plan was finalized in November 2015 and then entered the implementation stage.

Multiple sources of data were collected on this case, as recommended by Yin (2003): 1) process documents including enacting and related legislation, interim progress reports, major press releases, and final public “output” documents from the websites associated with the CWCB and State of Colorado; 2) two rounds of semi-structured, qualitative interviews (Rubin and Rubin 2005) with process participants (n = 40); and 3) a quantitative survey of Roundtable process participants (n = 111), which allowed the researcher to determine if themes from the qualitative interviews were also seen across a broader sample of process participants. During the course of the study, the researcher also attended meetings with 7 of the 9 Roundtables, two IBCC meetings, and a variety of statewide events that brought process participants from the

Roundtables and IBCC together, to build an in-depth understanding of the process and trust with process participants.

Interview Data Collection and Analysis Methods

In 2013-2014, semi-structured interviews (n = 28) were conducted with key participants across the stakeholder groups and geographical areas encompassed by each Roundtable (Table 1). These interviews occurred in the period the between the issuance of the governor's executive order (a key moment that catalyzed collaboration among stakeholders in each Roundtable) and the production of individual BIPs (the formal documentation of collaboration). Interview questions focused on stakeholders' roles, perceptions of the process, interactions with other stakeholder groups, and outputs of the process. The data from these interviews were used in a preliminary qualitative examination of Hypotheses 1-3 (Koebele Under Review).

This qualitative data set was expanded through the inclusion of additional in-depth interviews (n = 12) that were conducted after the release of the CWP in 2016 (Table 1). Interviewees include key participants who helped finalize the plan, including staff at the CWCB and the Colorado Department of Natural Resources, as well as key stakeholder group leaders involved in the Roundtables and IBCC. While these interviews focused on similar topics as the previous round (e.g., process goals and how they were achieved, patterns of collaboration among stakeholders, and the implementation of outputs), they sought to further specify themes that were broadly mentioned in the initial round of 28 interviews, including the types of learning that process participants experienced.

Table 1. Rounds 1 and 2 Interview Subjects

Interview Round (year)	Interviewee Group/Designation	Total Interviews
1 (2013-2014)	Arkansas Basin	3
	Colorado Basin	4
	Gunnison Basin	3
	Metro Basin	4
	North Platte Basin	3
	Rio Grande Basin	3
	South Platte Basin	3
	Southwest Basin	3
	Yampa/White Basin	3
	TOTAL	**29**[a]
2 (2016)	Colorado Water Conservation Board (CWCB)	6
	Colorado Department of Natural Resources (DNR)	1
	Non-Consumptive Use Stakeholders	1
	Consumptive Use Stakeholder	4
	TOTAL	**12**[b]

[a]One interviewee declined to be recorded; thus, the interview was not formally analyzed with the other 28.
[b]Participants in Round 2 interviews are assigned to a category based on their position during the final stages of development of the CWP; however, a number of these individuals have worked in/across multiple categories over the lifetime of the IBCC/Roundtable process and contributed broader perspectives on the process as a result.

Prospective interview participants were initially identified through process documents (including publically available lists of names and contact information) and during preliminary background discussions with key informants who participated in the collaborative process. Snowball sampling (Auerbach and Silverstein 2003), a process which interviewees are asked to identify other key participants in their process, was also used to expand the original sample. Subjects were selected to ensure representation of all relevant stakeholder groups in both rounds. Interviews were conducted both in person (n = 17) and via phone/Skype (n = 23), although the researcher met nearly all participants in person as part of the research project.

The interviews were digitally recorded, transcribed, and coded using QSR NVivo 10 qualitative analysis software. Codes for each round of interviews were developed *a priori* from the relevant literature on the ACF and collaborative processes. In the initial round of interviews, learning was coded for broadly as an outcome of the process as part of an examination of policy outputs, outcomes, and barriers to collaboration (Koebele 2015). In the second round of interviews, different aspects of learning were explicitly coded for in order to further specify this construct. For example, the supercode LEARN captured examples of self-described learning with subcodes for learning that occurred within a coalition, across coalitions, or by an external actor (i.e., the public). The coded data were analyzed by hand and using code queries in NVivo to detect patterns related to the hypotheses (Miles and Huberman 1994). To demonstrate that the qualitative information used in this paper was gathered from a variety of respondents, interview quotations from Round 1 interviews are designated by their Interviewee Group/Designation shown in Table 1 (i.e.,Yampa-White Basin). Quotations from Round 2 interviews are designated as “CWP” rather than by a specific Interviewee Group/Designation, followed by a randomly assigned number (1-12), in order to preserve anonymity in a smaller group of interviewees. While these interview data were primarily used to inform the development of survey items (more on this below), they also allowed the researcher to understand the case study in depth and gather information that is helpful in interpreting the quantitative results of the survey.

Survey Data Collection and Analysis Methods

A survey questionnaire was then developed based on major themes identified through the 40 qualitative interviews (more below). The survey sample population included the 341[2] members of the IBCC and Roundtables in 2016. A link to the electronic questionnaire was distributed to the sample population via an email from the CWCB. Three reminders were sent via email from the CWCB to all members of the sample population using varying message content in order to maximize response rate, as suggested by Dillman, Smyth, and Christian (2009). Messages were kept as concise as possible and were delivered to recipients in the morning (between 6:45 and 10:15am) on varying days of the week. One additional reminder was sent

[2] The email was initially sent to 344 individuals, but 3 individuals indicated on the survey that they had not participated in the Roundtable/IBCC process and were thus removed from the sample.

directly from the researcher to the chair of each Roundtable, requesting that the chair personally invite his or her Roundtable's membership to participate in the survey. This also established an avenue for the chair to ask any questions of the researcher if they arose from the Roundtable membership. Prior to dissemination to the sample population, the questionnaire was completed and reviewed by five individuals in the academic and public spheres who have extensive knowledge of the Roundtable process and Colorado water governance issues in order to ensure the language and concepts in the survey are consistent with those used by the sample population. They were not part of the sample population, nor are their responses included in the data set analyzed here.

The response rate was 32.6%, with 111 respondents completing some portion of the content-based survey questions beyond the initial consent question. Ninety-five surveys were fully completed. This response rate is similar to that seen in previous surveys of this population (Crow and Baysha 2013). The respondents were fairly representative of the population expected to participate in water policy negotiations in the West (Table 2). Regarding political affiliation, respondents mirror Colorado's fairly equal division between Democrats, Republicans, and Independents. More males participated in this process than females, reflecting the fact that water policymaking in Colorado has historically been male-dominated. The sample is highly educated and dominated by people who have worked in Colorado water matters for more than 11 years (i.e., longer than the process has existed), likely reflecting the fact that such a time-intensive governance process draws attention from professionals who are already interested in or involved in the topic. There is also a slight skew toward residents of the Western Slope versus other regions of Colorado, but this is unsurprising considering that 4 of the 9 Basin Roundtables are located within this region. Figure 1 depicts survey responses by Roundtable/IBCC membership, with the number of respondents listed next to each group name.

Table 2. Descriptive Statistics of Survey Respondents

Political Affiliation[a]	Democrat	Republican	Independent	Other			
	33% (30)	33% (30)	30.8% (28)	2.7% (3)			100% (91)
Gender	Male	Female					
	78.1% (75)	22.9% (21)					100% (96)
Education[b]	High School	Some College	4-year College Degree	Graduate Degree	Professional Degree		
	3.1% (3)	10.4% (10)	33.3% (32)	37.5% (36)	15.6% (15)		100% (96)
Years Worked in CO Water Matters	<2	2-5	6-10	11-15	16-20	20+	
	1% (1)	3.1% (3)	9.4 (9)	10.4 (10)	12.5 (12)	63.5 (61)	100% (95)
Colorado Region Of Residence	W. Slope/ Central Mtns	Metro Front Range	E. Plains/ NE CO	S. CO/ San Luis Valley			
	47.9% (46)	25% (24)	10.4% (10)	14.4% (16)			100% (96)

[a] According to the Colorado Secretary of State (2017) tally of active registered Colorado voters as of January 2017, 31.8% are Democrats, 31.6% are Republicans, and 34.7% are Independent/Unaffiliated. The remaining ~2% are registered with other parties.

[b] According to the U.S. Census Bureau (2017) statistics from 2011-2015, 38.1% of Coloradoans aged 25+ have a bachelor's degree or higher.

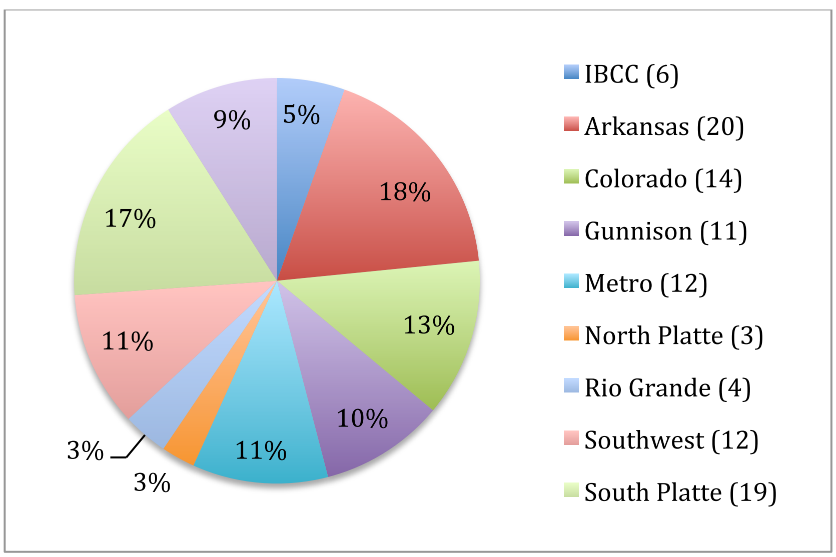

Figure 1: Survey Participation by Group Membership. Western Slope Basin Roundtables include the Colorado, Gunnison, Southwest, and Yampa-White Roundtables.

Questionnaire Content based on Interview Data

The survey questionnaire was broad in scope, asking respondents to answer questions about whom they collaborated with and how, what they learned, and what effects the process has had on water planning and management in Colorado thus far. The remainder of this section will describe in detail the specific items used for the analysis that follows, including the qualitative data that was used to develop the survey items. Respondents were asked to rate statements on a Likert scale, where 1 = strongly disagree to 5 = strongly agree. The items as they appeared in the survey, along with their means (M), standard deviations (SD), and internal reliability for multi-item variables (Cronbach's α), are listed in Table 3.[3]

The first five items represent procedural features directly related to Hypotheses 1-3, including the presence of consensus-based decisionmaking (H1), face-to-face interaction (H2), strong leadership (H2), multiple information sources (H3), and opportunities to deliberate (H3). These items, are designed to measure mechanisms underlying *learning processes* (the acquisition, translation, and dissemination of information). Following Heikkila and Gerlak (2013), a hard distinction between procedural features influencing individual and collective learning is not made due to the assumption that learning occurs at multiple, interacting levels that are not truly separable in collective policy contexts. A higher score on these items indicates that the variable was present to a greater degree in the collaborative process that the respondent participated in. These factors were developed from the literature and responses to interview questions about what features of the Roundtable process encourage collaboration among diverse actors. For example, participants explained:

[3] Respondents' scores on some of the items were re-coded in the process of forming composite variables. Information on re-coding is included in the description of each variable below. The means and standard deviations included in Table 3 are for the processed (re-coded, composite) variables.

Table 3: Summary of Variables and Items of Interest

Theoretical Concept	Variable	Item(s)	M (SD)	α
Procedural Features	Consensus	My group makes decisions based on consensus.	4.23 (.07)	N/A
	Face-to-Face Interaction	My group encourages face-to-face interaction.	4.08 (.07)	N/A
	Strong Leadership	My group has a strong leader.	3.88 (.08)	N/A
	Diverse Information	My group welcomes different types of information (scientific, experiential, personal values/perspectives) into our discussions.	4.04 (.08)	N/A
	Information Deliberation	My group creates ample opportunities to openly deliberate on the information that is brought to the table.	3.95 (.08)	N/A
Policy-Oriented Learning	Individual Learning (Products)	I have a better understanding of water as a physical resource in Colorado. I have a better understanding of the laws and policies that govern water in Colorado. I have a better understanding of other stakeholders' values and needs regarding water in Colorado. I have a better understanding of what actions are politically feasible. I am better prepared to effectively participate in other collaborative governance processes in the future.	6.19 (.23)	.818
Policy Change	Collective Learning (Products)	The process has generated innovative solutions that would not have happened without the Roundtables and IBCC. The decisions/plans arising from the process contribute to increasing the sustainability of water resources in Colorado. The process has improved water planning in Colorado. The decisions/plans devised by the process fail to tackle the state's major issues related to managing water resources. [reverse coded] The process has brought new perspectives into water discussions and planning in Colorado. The process has expanded the scope of participants (new stakeholders and the public) in the dialogue about water in Colorado. The decisions/plans arising from the process usually work in favor of one group of stakeholders more than others. [reverse coded]	5.98 (.34)	.860
Other	Collaborative Preferences	It is positive to have a wide variety of stakeholders with different viewpoints at	16.06 (.24)	.719

	the table in a water-related decision-making process.
	A collaborative-type process is more useful than a top-down regulatory-type process for making decisions about water at the basin scale.
	The time it takes to come to an agreement on decisions in a collaborative process is not worth the outcome. [reverse coded]
	Collaborative decision-making processes end up too mired in conflict to actually make decisions. [reverse coded]

> The way the Roundtable process was set up is, 'we will force you to **sit together {face-to-face interactions}**, you will not be all be of the same perspective, we will **give you time to agree {reach consensus}** on what your needs are across all of those different perspectives, we will help you experiment about what the tradeoffs are between the different solutions… we will expect that you will make your decisions based off of **good information {information sources}**. We will give you deadlines and we will promise that it's really up to you to fill in the content once we've given you the structure and the deadlines.' (CWP_12)

> It is some of the nuances that I think that **we're able to kind of overcome with discussion {deliberation}**. You can't do it in one meeting, but over several years… (CWP_1)

> I think **well-facilitated meetings {strong leadership}**… that was part of it too. They weren't just thrown in a room and told to work things out… a lot of people made a lot of money facilitating these meetings, so it was a huge investment. (CWP_8)

The Individual Learning variable serves as a measure of an individual's policy-oriented learning as a result of their participation. The items related to the Individual Learning variable attempt to capture the categories of knowledge that respondents gain as a result of their participation, i.e., their *individual learning products*. This includes learning about the resource, the relevant policy, other stakeholders' values, the feasibility of various solutions, and how to more effectively participate in the process. These categories were informed by the literature and responses to interview questions about what individual participants have learned in the Roundtable process:

> I think every one of us has learned a lot about other areas of the basin and **how the water is used and why the water is used this way {resource and relevant policy}**, and where the shortages exist and how they could be solved… (Gunnison Basin)

> I think [the Roundtable process has] really been successful on…understanding the perspectives of other individuals {others' values}, whether it's [municipal and industrial], or [agriculture], or nonconsumptive uses and how we have to coexist and how we have to work together, **and how can we best utilize the resource** {**resource}**. (Arkansas Basin)

> At least we know the people who are talking about that and we understand their needs. We understand, you know, what their [water supply] gap is **{resource, others' values}**. And I think that's going to improve the likelihood that we can come together on a balanced solution. (Colorado Basin)

> I do think there was some good listening that happened and maybe some, as a result of that listening, some increased understanding of the concerns and goals of the various partners around the table **{others' values}**. (CWP_10)

> There's probably a slight increase in the degree of realism and practicality that both sides realize **{feasibility of solutions}**. You're not going to move a water project forward until you do address the environmental… And at the same time the environmentalists need to find ways that – maybe they can't protect every mile of every stream but there's some critical areas that they need to protect. Maybe there's ways to operate a project that provides some additional benefits. (CWP_7)

> And so I think what the Water Plan has done is give us a platform to talk about these ideas and figure out where the **regulatory barriers {relevant policy and feasibility}** to those are, because they're significant. (CWP_3)

> **I've learned how to do it better {effective participation}**. Without the opportunity to do—to participate in some kind of consensus-based… consensus-based mechanism with this level of complexity and these problems, I don't think you get very good at it. (Yampa-White Basin)

Respondents' scores on each item were re-coded so that strongly agree = 2, agree = 1, and all other responses = 0 in order to separate those who learned to some degree (about any of the individual categories of knowledge) from those who did not. Re-coded scores on the five items were summed, producing a variable (range 0-10) where a higher score indicates more individual learning in comparison to no learning.

The Collective Learning variable serves as a measure of policy change, broadly defined, resulting from a collaborative process. The items related to the Collective Learning variable represent respondents' perceptions of the *collective learning products* that have arisen from the collaborative process.[4] Collective learning products include everything from new collective expectations about the decisionmaking process (e.g., including a broader scope of participants and perspectives) to plans/policies arising from the process and their impacts on relevant social/natural environments (e.g., improved planning, innovative solutions that tackle important issues and benefit multiple groups, increased resource sustainability). While it remains to be seen if the solutions proposed in the CWP can truly tackle the state's biggest water issues, a number of second-round interviewees commented on collective behavioral changes it had immediately provoked:

> And you've got everybody talking about **"multi-purpose projects"** which used to mean [agriculture] and [municipal], and now very clearly means ag, muni, and environment **{solutions working in favor of more than one group}**. So we've moved the needle on that to some extent. (CWP_10)

> The other fundamental thing that changed was prior to [the process], the water community was extraordinarily small and extraordinarily—not only parochial, but insular. There was no connection with the rest of the state—very few people understood. **So one of the true benefits of [the process] was expanding the discussion to much larger group of people from various communities {new perspectives and expanded scope of participants}**. (CWP_8)

> And so, we're optimistic that the plan aims us at the right direction and that it does begin to paint a picture of what things should look like in terms of water management for our state. That would not—we **didn't have that before the plan {innovative solutions that would not have otherwise happened}** and I think now we have a better one that could be improved on. (CWP_6)

[4] Gerlak and Heikkila (2011) acknowledge that collective learning products is a "generic term that encompasses many different types of collective changes in knowledge, program strategies, or policies" (622). While cognitive changes typically lie outside of the umbrella of policy change, making the comparison between these two terms imperfect, the measures of collective learning used in this study focus on the behavioral (institutional/policy) change aspects of the term rather than the cognitive aspects.

> Even if they've done it that way for twenty years, **they've got to be able to change that… it shouldn't just be unilateral decisions** made by the Division about how we [make plans/policies] **{improved planning}.** (CWP_5)

Similar to the Individual Learning variable, respondents' scores on each item related to Collective Learning were re-coded so that strongly agree = 2, agree = 1, and all other responses = 0 in order to separate those who perceived some degree of collective learning from those who did not. Re-coded scores on the seven items were summed, producing a variable (range 0-14) where a higher score indicates a greater perception of collective learning compared to those who perceived no learning.

Finally, the items related to the Collaborative Preferences variable gauge a respondent's innate proclivity toward or preference for collaborative approaches to decisionmaking. This variable serves as a control in the analyses that follow. Respondents' raw scores on the four items were summed, producing a variable (range 5-20) where a higher score indicates greater preference for collaborative approaches.

As can be seen in Table 3, responses to these items were generally positively skewed, except in the case of Collective Learning. This suggests that some of these items may fall victim to social desirability bias, a phenomenon in which respondents "admit to socially desirable traits and behaviors and also deny socially undesirable ones" (Krumpal 2013, 2028). In other words, respondents may be more inclined to "agree" with items such as their group coming to consensus, because this trait, for example, is often described as "not merely a logical and inevitable product of the search for truth, but is something with a strong social value" (Kenney 2000, 41). In other words, "consensus" is something that is *supposed to* result from collaborative processes, so respondents may be more inclined to say that their collaborative group does indeed achieve it. Due to the non-normal distribution of these variables, understanding variability at the high end of the data (i.e., between respondents who “agree” with certain items, perhaps simply conforming to a socially-desirable standard, and those who “strongly agree,” potentially emphasizing that the statement is truly representative of their process) is particularly important. Due to their high skew toward positive responses, items related to procedural features and individual learning (where respondents potentially feel more personally implicated) appear to be more prone to social desirability bias as opposed to questions related to the products of the process (where the collective is implicated more than the individual), which tended to have a less skewed distribution; however, it is possible that these products simply solicited a wider range of agreement and disagreement from survey respondents.

Results and Discussion

The survey data were analyzed using SPSS statistical software. Individual analyses pertaining to the hypotheses are presented in the following sections. For all analyses, pairwise deletion was used to deal with missing data, meaning that as long as a respondent answered all questions relevant to a specific statistical test, their responses were included in the analysis.

Bivariate Correlations

Table 4 displays the bivariate (Pearson product-moment) correlations among the study variables. Those who experienced a greater degree of Individual Learning tended to have higher innate Collaborative Preferences, stated that the procedural features asked about were present to a greater degree, and perceive a greater degree of Collective Learning. Differences in learning between groups on a number of demographic variables (gender, age, political affiliation, education, region of residence) were tested using ANOVA analyses, but none were found to be significant and were therefore not included in the analyses that follow. However, gender (which was not significantly correlated with any of the other study variables) was still included due to the theoretical assumption that men and women may have different interpersonal skills and preferences and may therefore experience learning differently in collaborative contexts that rely heavily on discussion and deliberation.

Table 4: Correlations Between Study Variables

	1	2	3	4	5	6	7	8	9
1. Consensus	--								
2. Face-to-Face Interaction	.482**	--							
3. Strong Leadership	.242*	.350**	--						
4. Diverse Information	.452**	.597**	.337**	--					
5. Information Deliberation	.516**	.654**	.505**	.592**	--				
6. Individual Learning[a]	.277**	.233*	.218*	.373**	.234*	--			
7. Collective Learning[a]	.264**	.278**	.243*	.363**	.236*	.643**	--		
8. Collaborative Preference[a]	.176	.416**	.252*	.298**	.215*	.421**	.451**	--	
9. Gender (ref = male)	-.149	-.034	.061	-.047	-.148	.115	-.021	.156	--

**$p \leq .01$, *$p \leq .05$; a = variable is a composite of two or more items
Note: n's range from 92 to 107 depending on missing data.

Collinearity Testing and Factor Analysis

All of the procedural feature variables (Table 3, variables 1-5), which would be the predictors in analyses testing H1-H3, are significantly correlated and most are strongly correlated ($r \geq .3$), suggesting some of the constructs are not independent of one another. As a result, a collinearity test was conducted. Because all variables achieved a Tolerance greater than .1 (values = .512-.785), and relatedly, a VIF less than 10 (values = 1.273-1.953), multicollinearity among these variables was rejected.

To further understand the relationship among the predictor variables, a factor analysis was conducted using principal-axis factoring and an oblique (direct oblimin) factor rotation (due to the non-normal distributions of the variables and the expectation that multiple factors, if they exist, will be highly correlated with one another). The analysis produced only one factor with an eigenvalue greater than 1.0. Four of the five variables loaded onto the factor at a value ≥ .55 (Table 5), which is recommended by Hair et al. (1988) as the appropriate factor loading in studies where n = 100 (104 respondents answered all five of the items included in the factor analysis). When “Strong Leadership” is removed from the factor analysis, the factor explains 66.5% of the total variance in the items (eigenvalue = 2.66). A reliability analysis was then performed to examine the internal consistency of the four remaining items, which revealed that the items form a reliable scale (Cronbach’s α = .830).

Table 5: Principal-Axis Factor Loadings with Direct Oblimin Rotation

Variable	Factor 1
Consensus	**.605**
Face to Face Interaction	**.784**
Strong Leadership	.488
Diverse Information	**.719**
Information Deliberation	**.861**

In response to these results, a variable called “Institutional Features” was created by summing respondents’ scores on the four procedural feature variables that loaded onto Factor 1. This factor reflects features inherent to the institutional design of a collaborative process (i.e., the rules and norms of the process). These features may exist whether or not the process has Strong Leadership, which remains its own unique predictor variable in the analyses going forward. See Table 6 for revised bivariate correlations using the Institutional Features (F1) variable.

Table 6: Revised Bivariate Correlations Between Study Variables

	1	2	3	4	5	6
1. Institutional Features (F1)	--					
2. Strong Leadership	.446**	--				
3. Individual Learning[a]	.363**	.218*	--			
4. Collective Learning[a]	.356**	.243*	.643**	--		
5. Collaborative Preference[a]	.363**	.252*	.421**	.451**	--	
6. Gender (ref=male)	-.135	.061	.115	-.021	.156	--

**$p \leq .01$, *$p \leq .05$, a = variable is a composite of two or more items
Note: n’s range from 91 to 107 depending on missing data.

In these revised correlations, Institutional Features and Strong Leadership are both correlated with Individual Learning (H1-3), and Individual Learning is correlated with Collective Learning (H4). The fact that Institutional Features remains highly correlated with Strong Leadership, r (104) = .446, $p \leq .01$, suggests that a respondents’ perception of leadership may not be uniquely important to understanding their learning in the presence of the other institutional features.

Intraclass Correlation Testing

Due to the clustered nature of the data (i.e., respondents belong to groups—either one of nine Basin Roundtables or the IBCC), it is necessary to determine if scores on the two dependent variables (Independent Learning for H1-3 and Collective Learning for H4) are more similar within groups than they are across groups. An Intraclass Correlation (ICC) analysis produced a correlation coefficient near 0 ($\rho = -.09$) for both the Individual Learning and Collective Learning variables, and design effects of .15 and .25 respectively. These scores fall below the threshold of a design effect of 2 that is commonly used to determine when multi-level modeling is needed to cope with cluster effects, allowing the researcher to proceed with regular multiple regression techniques to test the dependent variables individually.

Predicting Policy-Oriented Learning (Hypotheses 1-3)

A multiple linear regression was performed to understand how a respondent's Individual Learning (suggested here to be representative of the theoretical concept of policy-oriented learning) is related to their scores on Institutional Features (F1), Strong Leadership, Gender, and Collaborative Preference. A two-stage model was run in which Gender and Collaborative Preference (controls) were entered into Model 1. Institutional Features and Strong Leadership (predictors) were then entered into Model 2. The results are summarized in Table 7.

Table 7: Multiple Linear Regression Analysis Predicting Individual Learning

	Model 1				Model 2			
Variable	B	SE	β	p	B	SE	β	p
Gender (ref=male)	.285	.551	.051	.517	.566	.553	.100	.309
Collaborative Preference	**.969**	**.229**	**.413**	**≤ .01**	**.721**	**.244**	**.308**	**≤ .01**
Institutional Features (F1)					**.600**	**.265**	**.256**	**≤ .05**
Strong Leadership					.048	.250	.020	.849
Adjusted R^2		.161				.203		
F for Change in R^2		9.651		≤ .01		**3.307**		**≤ .05**

Note: Standardized scores (z-scores) were used for Institutional Features, Strong Leadership, and Collaborative Preference.

Model 1 is significant, $F(2, 88) = 9.651$, $p \leq .01$, revealing that Collaborative Preference contributes unique, positive variance to the model. Model 2 is also significant $F(4,86) = 6.732$, $p \leq .01$, revealing that Institutional Features also contributed unique, positive variance to the model. In other words, both Collaborative Preference and Institutional Features significantly and individually predict Individual Learning when all other variables are controlled for. The change in R^2 between the models is significant at the $p \leq .05$ level, indicating that Model 2 explains significantly more variance in learning (about 4%) than Model 1.

Because the items representing Consensus, Face-to-Face Interaction, Information Diversity, and Information Deliberation were collapsed into a factor-based variable (Institutional Features) to conduct this analysis, the model does not allow for the testing of Hypotheses 1-3 individually. However, a respondent's Institutional Features score significantly predicts their Individual Learning score, thereby lending preliminary support for the hypotheses, at least when a process implements most of the collaborative features simultaneously. Importantly, a person's innate Collaborative Preference also significantly influences how much they learn, supporting the assumption that some people may simply be more "primed" to learn when they enter a collaborative process than others, regardless of the procedural features of the process.

A number of interaction terms were also tested to further explore the relationships among predictor variables (Table 8). The interaction between Institutional Features and Strong Leadership (Model 2a) was significant, as was the interaction between Collaborative Preference and Strong Leadership (Model 2b).

Table 8: Multiple Linear Regression Analysis Predicting Individual Learning with Significant Interaction Terms

	Model 2a				Model 2b			
Variable	B	SE	β	p	B	SE	β	p
Gender (ref=male)	.786	.545	.139	.152	.418	.545	.074	.446
Collaborative Preference	**.681**	**.237**	**.290**	**≤ .01**	**.797**	**.241**	**.340**	**≤ .01**
Institutional Features (F1)	**.764**	**.266**	**.326**	**≤ .01**	**.580**	**.259**	**.247**	**≤ .05**
Strong Leadership	.115	.244	.049	.472	.132	.247	.056	.594
Institutional * Leadership	**.382**	**.154**	**.242**	**≤ .05**				
Preference * Leadership					**.450**	**.204**	**.209**	**≤ .05**
Adjusted R^2		.248				.237		
F for Change in R^2 (from Model 2)		**6.137**		**≤ .05**		**4.850**		**≤ .05**

Note: Standardized scores (z-scores) were used for Institutional Features, Strong Leadership, and Collaborative Preference.

The Strong Leadership variable has a similar moderating effect on the relationship between both significant predictor variables (Institutional Features and Collaborative Preference) and the dependent variable (Individual Learning), as shown in Figures 2a and 2b. In both instances, when a respondent scores low on either predictor variable, participating in a process with Strong Leadership has a somewhat negative effect on their learning. One potential explanation for this is that a person who does not inherently prefer a collaborative approach or does not feel that his or her group employs strong Institutional Features may be more hostile toward the process and the possibility of learning from it when a particularly strong leader is goading them into collaboration. However, when a respondent scores high on either independent variable, Strong Leadership can increase the amount they learn. However, when both interaction terms are put into the same model, neither is significant.

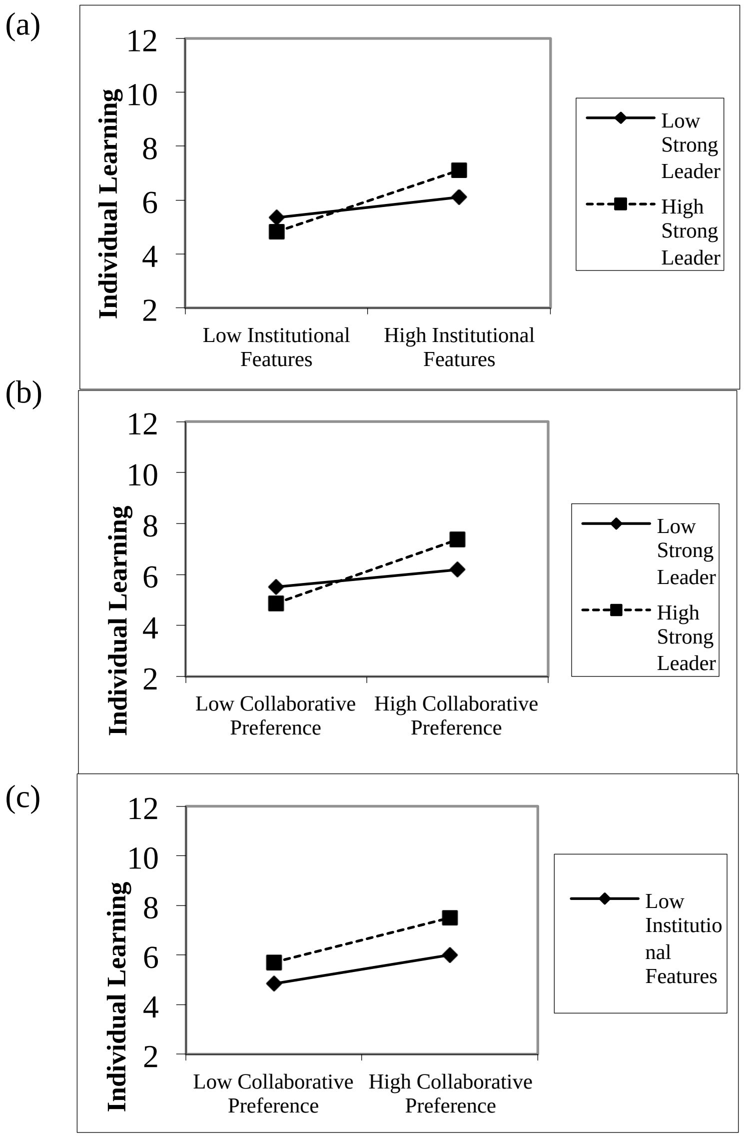

Figure 2: Two-way Interaction Effects for Standardized Variables

While the interaction between Institutional Features and Collaborative Preferences is not significant (and is not shown in a model here), the results suggest that Institutional Features may moderate the effect of Collaborative Preferences on learning (Figure 2c). For instance, among those who have lower a Collaborative Preference, individuals who score higher on Institutional Features learn more. As suggested by one interviewee, many people enter collaborative processes such as the Roundtable process with the intent to defend their own interests rather than the desire to collaborate. This can lead to a hurting stalemate between traditionally conflicting sides where policy change is difficult to achieve. However, having a process with strong Institutional Features may help even those who have a low Collaborative Preference learn more and become engaged in finding productive solutions:

> Water is very much a personality-driven, personal relationship deal. If you have those [moments where people come together to talk], you have at least the chance of coming to consensus. If you don't have those, you have no hope. There's just no way it's going to happen because people will automatically fall back to their personal interest of trying to get something out of it for their agency of their organization or them personally. If you play the game, you quickly fall victim to a prisoner's dilemma where nobody comes out with the best alternative. (CWP_5)

Moreover, those with a high Collaborative Preference also learn more in the presence of these Institutional Features, suggesting that such features benefit all participants in the process, not just those who show initial resistance. This interaction should be further tested in a study with a larger sample size to determine if the difference in Individual Learning is significant under varying strengths of Institutional Features.

Predicting Policy Change (Hypothesis 4)

Next, a second multiple linear regression was performed to understand if a respondent's perception of Collective Learning (suggested here to be representative of the theoretical concept of policy change) is predicted by their scores on Individual Learning (policy-oriented learning), as proposed in Hypothesis 4. Control variables from the previous regression models (Gender, and Collaborative Preference) were maintained here. A three-stage model was run in which Gender and Collaborative Preference (controls) were entered into Model 3. Institutional Features and Strong Leadership (predictors) were entered into Model 4. Individual Learning (predictor) was then entered into Model 5. The results are summarized in Table 9.

Table 9: Multiple Linear Regression Analysis Predicting Collective Learning

	Model 3				Model 4			
Variable	B	SE	β	p	B	SE	β	p
Gender (ref=male)	-.749	.768	-.093	.332	-.480	.799	-.060	.539
Collaborative Preference	**1.549**	**.319**	**.465**	**≤ .01**	**1.255**	**.343**	**.377**	**≤ .01**
Institutional Features					.597	.373	.179	.113
Strong Leadership					.238	.351	.072	.499
Individual Learning								
Adjusted R^2		.194				.218		
F for Change in R^2		11.809		≤ .01		2.341		.102

Note: Standardized scores (z-scores) were used for Collaborative Preference and Individual Learning.

	Model 5			
Variable	B	SE	β	p
Gender (ref=male)	-.914	.661	-.114	.171
Collaborative Preference	**.703**	**.304**	**.211**	**≤ .05**
Institutional Features	.137	.324	.041	.673
Strong Leadership	.202	.297	.061	.498
Individual Learning	**1.796**	**.300**	**.539**	**≤ .01**
Adjusted R^2		.443		
F for Change in R^2		**35.754**		**≤ .01**

Note: Standardized scores (z-scores) were used for Collaborative Preference and Individual Learning.

Model 3 is significant, $F(2, 88) = 11.809$, $p \leq .01$, and reveals that Collaborative Preference contributes unique, positive variance to the model. Model 4 is also significant, $F(4, 86) = 7.255$, $p \leq .01$, but neither of the two added predictors contributes unique variance to the model, and the change in R^2 between Models 3 and 4 is not significant. Model 5, however, is significant, $F(5,85) = 15.300$, $p \leq .01$, and reveals that Individual Learning contributes unique, positive variance to the model. In other words, both Collaborative Preference and Individual Learning significantly and individually predict learning when all other variables are controlled for in the final model. The change in R^2 between the Model 4 and Model 5 is significant at the $p \leq .01$ level, indicating that Model 5 explains significantly more variance (about 22.5%) in perceptions of Collective Learning than Model 4. The interactions between Collaborative Preference and Individual Learning, as well as between Institutional Factors and Individual Learning, were tested but are not significant and are therefore not shown here.

The results of Model 5 support Hypothesis 4, indicating that a greater degree of policy-oriented learning (i.e., Individual Learning) predicts greater policy change (i.e., Collective Learning). In the final model, Collaborative Preference remains a significant predictor of Collective Learning (β = .211), but to a smaller degree than Individual Learning (β = .539). This may be because Collaborative Preference is a strong indicator of Individual Learning, which strongly predicts Cognitive Learning. Importantly, people with a stronger Collaborative Preference may tend to rate the outcomes of a collaborative process more highly, a phenomenon known as the Halo Effect (Leach and Sabatier 2005); however, the greater variance and more normal distribution of scores on Collective Learning, as opposed to scores on Collaborative Preference with lower variance and a more skewed distribution, suggests that this may not actually be the case. Finally, Institutional Factors and Strong Leadership are not significant in any of the models predicting Collective Learning, suggesting that these procedural factors (representation of the mechanisms underlying individual and collective learning processes) may influence Individual Learning, which appears to be an important precursor to Collective Learning, but do not influence Collective Learning directly.

Conclusion

Taken together, the results of this analysis speak to the study's main research question: *what procedural features increase policy-oriented learning in collaborative processes, and does policy-oriented learning lead to policy change.* Model 2 suggests that certain institutional features such as consensus-decisionmaking norms, face-to-face interactions, diverse information, and opportunities to deliberate increase policy-oriented learning on the individual level (i.e., individual learning products), but Models 4 and 5 suggest that they may not have the same effect on collective learning products. This underscores the need to understand if there is indeed a unique collective learning *process* that links individual learning products with collective learning products and what procedural mechanisms may underlie it. Additionally, while participating in a process with Strong Leadership was significantly correlated with both Individual and Collective Learning, it was not a significant predictor of either type of learning (Models 2 and 4), though it may have a moderating effect in some cases (Models 2a and 2b, Figure 2a and 2b). Furthermore, Individual Learning was a significant predictor of Collective Learning (Model 5). In other words, those who learned more individually perceived that their process produced greater collective learning products (cognitive and behavioral changes).

In light of these results, it is critical to note a number of drawbacks to this study that also serve as suggestions for future research. First, while the survey used in this study did achieve a satisfactory response rate from participants within a singular collaborative governance process, allowing the researcher to inherently control for important process-wide variables that would not be possible in a multi-case study, some of the analyses were constrained by both a relatively small sample size and highly skewed data on key items. This resulted in having to combine multiple predictor variables into one composite variable (“Institutional Features”) using factor analysis. Practically, this suggests that researchers must continue to find new ways to increase their sample size in studies of collaborative processes, even when their response rate is satisfactory. It also suggests that researchers studying collaborative processes must continue to refine their measures of these somewhat ambiguous concepts to be more sensitive while keeping in mind that survey questions related to both individual learning and the institutional features of a policy process may suffer from issues of social desirability bias.

On a theoretical level, these issues suggest that the ACF's hypotheses about policy-oriented learning (and the adapted ACF hypotheses tested here) may over-specify the conditions under which a person or group may learn, and consequently, that learning may need to be examined as a holistic consequence of multiple, interacting individual and institutional factors as opposed to being driven by a smaller number of separate, easily-specified features. In other words, it is possible that collaborative processes can do a number of different things to increase general "collaborativeness" of the process to a level that promotes learning, rather than using a specific "recipe" of institutional features that are each deemed necessary for learning.

Additionally, as alluded to above, while the Collective Learning (products) variable captures both collective cognitive and behavioral (i.e., institutional/policy) changes at the collective level, the variable used here measures a respondent's *perception* of these changes. It does not measure actual change in collective knowledge (which must be defined more clearly and separately from individual knowledge) or the degree of behavioral change from a past state, which could potentially be measured through an analysis of policy outputs and outcomes to arrive at more robust understanding of learning and policy change. Once again, this conclusion has both practical and theoretical implications. Scholars studying collective learning need to find ways to more objectively measure collective changes in addition to respondents' perceptions of them. Additionally, for scholars interested in the ACF, work should be done to refine the ACF's definition of policy change to determine whether it includes both cognitive and behavioral (institutional/policy) changes on the collective level. This will allow for the further specification and testing of mechanisms underlying the policy-oriented learning pathway to policy change.

Acknowledgments: This work has been generously supported by the University of Colorado Boulder's Center for the Advancement of Research and Teaching in the Social Science (CARTSS), the University of Colorado Boulder's Graduate School, the Arkansas River Basin Water Forum, and the Horowitz Foundation for Social Policy. The author wishes to thank Dr. Amanda Carrico, Dr. Tanya Heikkila, Dr. Elizabeth Albright, Dr. Deserai Crow, Dr. Tomas Koontz, and anonymous reviewers for their valuable feedback.

References

Ansell, Chris, and Alison Gash. 2008. "Collaborative Governance in Theory and Practice." *Journal of Public Administration Research and Theory* 18 (4):543-71.

Colorado Water Conservation Board. 2016a. "Basin Roundtables." http://cwcb.state.co.us/water-management/basin-roundtables/Pages/main.aspx. (July 27, 2016).

Colorado Water Conservation Board. 2016b. "The Interbasin Compact Committee and Basin Roundtables." http://cwcb.state.co.us/about-us/about-the-ibcc-brts/Pages/main.aspx. (November 13, 2016).

Crow, Deserai Anderson, and Olga Baysha. 2013. ""Conservation" as a Catalyst for Conflict: Considering Stakeholder Understanding in Policy Making." *Review of Policy Research* 30 (3):302-20.

Dillman, Don A., Jolene D. Smyth, and Leah Melani Christian. 2009. *Internet, Mail, and Mixed Mode Survey: The Tailored Design Method.* 3rd ed. Hoboken, N.J.: John Wiley & Sons.

Emerson, Kirk, Tina Nabatchi, and Stephen Balogh. 2012. "An Integrative Framework for Collaborative Governance." *Journal of Public Administration Research and Theory* 22 (1):1-29.

Gerlak, Andrea K., and Tanya Heikkila. 2011. "Building a Theory of Learning in Collaboratives: Evidence from the Everglades Restoration Program." *Journal of Public Administration Research and Theory* 21 (4):619-44.

Gerlak, Andrea K., Tanya Heikkila, and Mark Lubell. 2013. "The Promise and Performance of Collaborative Governance." In *Oxford Handbook of U.S. Environmental Policy*, ed. S. Kamieniecki and M. E. Kraft. New York, NY: Oxford University Press. 413-34.

Hair, Joseph F., Rolph E. Anderson, Ronald L. Tatham, and William Black. 1988. *Multivariate Data Analysis*. 5th Edition ed. London, U.K.: Prentice Hall.

Heikkila, Tanya, and Andrea K. Gerlak. 2013. "Building a Conceptual Approach to Collective Learning: Lessons for Public Policy Scholars." *Policy Studies Journal* 41 (3):484-512.

Jenkins-Smith, Hank, C., Daniel Nohrstedt, Christopher M. Weible, and Paul A. Sabatier. 2014. "The Advocacy Coalition Framework: Foundations, Evolution and Ongoing Research." In *Theories of the Policy Process*, ed. P. A. Sabatier and C. Weible. Boulder, CO: Westview Press. 184-217.

Kenney, Douglas S. 2000. "Arguing About Consensus: Examining the Case against Western Watershed Initiatives and Other Collaborative Groups Active in Natural Resources Management." Boulder, Colorado: Natural Resources Law Center.

Koebele, Elizabeth A. 2015. "Assessing Outputs, Outcomes, and Barriers in Collaborative Water Governance: A Case Study." *Journal of Contemporary Water Research & Education* 155 (1):63-72.

Koebele, Elizabeth A. Under Review. "Using the Advocacy Coalition Framework to Understand Collaborative Policy Processes."

Koontz, Tomas M. 2014. "Social Learning in Collaborative Watershed Planning: The Importance of Process Control and Efficacy." *Journal of Environmental Planning and Management* 57 (10):1572-93.

Koontz, Tomas M. 2016. "Back to the Future? Collaborative Environmental Governance Theory and Practice." In *The Challenges of Collaboration in Environmental Governance: Barriers and Responses*, ed. R. D. Margerum and C. J. Robinson. Cheltenham, UK: Edward Elgar Publishing.

Koontz, Tomas M., and Craig W. Thomas. 2006. "What Do We Know and Need to Know About the Environmental Outcomes of Collaborative Management?" *Public Administration Review* 66 (s1):111-21.

Krumpal, Ivar. 2013. "Determinants of Social Desirability Bias in Sensitive Surveys: A Literature Review." *Quality & Quantity* 47 (4):2025-47.

Leach, William D., and Paul A. Sabatier. 2005. "Are Trust and Social Capital the Keys to Success? Watershed Partnerships in California and Washington." In *Swimming Upstream: Collaborative Approaches to Watershed Management*, ed. P. A. Sabatier, W. Focht, M. Lubell, Z. Trachtenberg, A. Vedlitz and M. Matlock. Cambrige, M.A.: MIT Press. 233-58.

Leach, William D., Christopher M. Weible, Scott R. Vince, Saba N. Siddiki, and John C. Calanni. 2014. "Fostering Learning through Collaboration: Knowledge Acquisition and Belief Change in Marine Aquaculture Partnerships." *Journal of Public Administration Research and Theory* 24 (3):591-622.

May, Peter J. 1992. "Policy Learning and Failure." *Journal of Public Policy*:331-54.

Miles, Matthew B., and Michael A. Huberman. 1994. *Qualitative Data Analysis: An Expanded Sourcebook*. Thousand Oaks, CA: Sage.

Muro, Melanie, and Paul Jeffrey. 2008. "A Critical Review of the Theory and Application of Social Learning in Participatory Natural Resource Management Processes." *Journal of Environmental Planning and Management* 51 (3):325-44.

Pahl-Wostl, Claudia, Marc Craps, Art Dewulf, Erik Mostert, David Tabara, and Tharsi Taillieu. 2007. "Social Learning and Water Resources Management." *Ecology and Society* 12 (2):5.

Pahl-Wostl, Claudia, David Tàbara, Rene Bouwen, Marc Craps, Art Dewulf, Erik Mostert, Dagmar Ridder, and Tharsi Taillieu. 2008. "The Importance of Social Learning and Culture for Sustainable Water Management." *Ecological Economics* 64 (3):484-95.

Raadgever, G.T., E. Mostert, and N.C. Van de Giesen. 2012. "Learning from Collaborative Research in Water Management Practice." *Water Resources Management* 26 (11):3251-66.

Rubin, Herbert J., and Irene S. Rubin. 2005. *Qualitative Interviewing: The Art of Hearing Data*. 2nd ed. London, UK: Sage.

Sabatier, Paul A., Will Focht, Mark Lubell, Zev Trachtenberg, Arnold Vedlitz, and Marty Matlock. 2005. "Collaborative Approaches to Watershed Management." In *Swimming Upstream: Collaborative Approaches to Watershed Management*, ed. P. A. Sabatier, W. Focht, M. Lubell, Z. Trachtenberg, A. Vedlitz and M. Matlock. Cambridge, Massachusetts: MIT press. 3-21.

Sabatier, Paul A., and Christopher M. Weible. 2007. "The Advocacy Coalition Framework: Innovation and Clarification." In *Theories of the Policy Process*, ed. P. A. Sabatier. Boulder, CO: Westview Press. 189-220.

State of Colorado. 2015. “Colorado’s Water Plan.” https://www.colorado.gov/pacific/cowaterplan. (July 27, 2016).

Weible, Christopher M., and Paul A. Sabatier. 2009. "Coalitions, Science, and Belief Change: Comparing Adversarial and Collaborative Policy Subsystems." *Policy Studies Journal* 37 (2):195-212.

Weible, Christopher M., Paul A. Sabatier, and Kelly McQueen. 2009. "Themes and Variations: Taking Stock of the Advocacy Coalition Framework." *Policy Studies Journal* 37 (1):121-40.

Yin, Robert K. 2003. *Case Study Research: Design and Methods*. 3rd ed. Thousand Oaks, CA: Sage Publications.